THE PSYCHOLOGY OF AGILE MARKETING: EXAMINING THE ROLE OF CONSUMERS' AFFECTIVE STATES AS DETERMINANTS OF REPURCHASE INTENTIONS IN MULTIBRAND FASHION APPS FROM THE UAE.

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A project submitted in partial fulfilment of the requirement for
the award of the degree M.A. STRATEGIC FASHION MARKETING
The London College of Fashion
University of the Arts London

30th September 2021

No portion of the work referred to in this project has been submitted in support of an application for another degree or qualification of this institution or any other university or other institution of learning.

In the writing of this project, I have received guidance from my supervisor, Dr. Cigdem Gogus and the MA faculty at London College of Fashion.

I, Rutuja Jadhav, certify that this is an original piece of work. I have acknowledged all sources and citations. No section of this MA project has been plagiarised.

Acknowledgement

I would like to thank my supervisor, Cigdem Gogus for her expertise and guidance throughout this project. I would also like to thank the rest of the faculty on the MA Strategic Fashion Marketing program for providing me with instrumental knowledge on the subject area during the course of my Master's degree.

Abstract

Given the rising levels of uncertainty during the COVID 19 pandemic, and highly competitive pureplay landscape, agility has been cited as a meritorious organizational trait particularly in fast-paced tech companies, to navigate changing consumer demands within a limited frame of time (Kotler, Kartajaya and Setiawan, 2021). From staying ahead of the latest trends, to personalizing the user journey with real time contextual updates, or even rapidly experimenting with content, agility has become an integral part of keeping pace with changing consumer preferences.

This study aims to investigate the effects of Agile Marketing Capabilities of multibrand fashion apps on the repurchase intentions of Gen Zs and younger Millennials, particularly accentuating on the intermediary role of consumer's affective states – pleasure, arousal, and dominance. Pureplay multibrand fashion apps refer to mobile platforms used by e-tailers such as ASOS and ZALANDO offering a plethora of brands under one umbrella. Equipped with mobility and rich data from the user's device, fashion apps provide an ideal context to study the effects of agile marketing on consumer behaviour.

Drawing on Mehrabian and Russell's (1974) theory of environmental psychology, this research builds on the Stimulus-Organism-Response and Pleasure-Arousal-Dominance frameworks to infer casual links between agile marketing capabilities of fashion apps, consumers' emotional states, and repurchase behaviour. In doing so, the study addresses limitations articulated in existing academia regarding lack of empirical research on agile strategies from a consumer perspective. Moreover, despite the growing number of users, fashion apps are still struggling with consumer retention due to emerging competitors and the increasing concerns around data privacy. Therefore, this study also adds to extant literature on app marketing by emphasizing on drivers of app usage continuance. In addition, this research particularly focuses on pureplay multibrand fashion apps in the UAE, as both pureplay multibrand fashion apps and the region of interest have received little attention in existing fashion academia.

The research adopts a positivist philosophy using mono-method deductive approach to validate hypotheses developed from theory. It further analyzes the data collected from an online questionnaire using statistical software to report empirical findings.

The novelty of this research stems from its context and is also observed in its key findings. This study illustrates the significance of feelings of dominance and arousal compared to feelings of pleasure, as the main determinants of repurchase intentions in fashion apps. It also demonstrates how agile cues such as newness of assortment and platform transparency act as precursors of such emotions. The study further uses such empirical findings to develop a conceptual model contributing to existing literature on fashion apps and agile marketing and provides strategic recommendations for app marketers to enhance app usage continuance.

Keywords: Agile Marketing Capabilities, Multibrand Fashion Apps, Repurchase Intentions, Consumer Psychology, Mobile Commerce, App Marketing .

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List of Abbreviations

AFS – After-Sales Service

AMC(s) – Agile Marketing Capabilities(s)

App – Application (Software)

ARO – Arousal

DOM – Dominance

E-Commerce – Electronic Commerce

M-commerce – Mobile Commerce

NoA – Newness of Assortment

PER – Personalization

PLE – Pleasure

PLS – Partial Least Squares

RPI – Repurchase Intentions

SEM – Structural Equation Modeling

TUX – Transparent User Experience

UBQ – Ubiquity

USD – United States Dollar

Chapter One INTRODUCTION

1. Introduction

"There is an app for that." – trademarked by Apple over a decade ago (Gross, 2010), the once highly popularized catchphrase has only become more relevant with time. As of 2020, the global mobile commerce (m-commerce) market is valued at USD 1,397,243.5 million (Euromonitor, 2021c). This is valuation comes with a total of 218 billion app installs worldwide (Statista, 2020). Although the mobile app market witnessed a 44% growth fueled by the COVID-19 pandemic in 2020 (Mintel, 2020), the app revolution has been equipping marketers and developers with rich consumer data from the 'always-on, constantly-connected since long before the onset of the pandemic shoppers' (Lamberton and Stephen, 2016; Lim *et al.*, 2021). The present study examines app marketing in the domain of pureplay multibrand fashion apps to elicit desirable consumer behaviour using agile marketing capabilities (further discussed below).

1.1. Context

1.1.1. App Marketing

According to Bellman *et al.* (2011) mobile apps can be defined as *'software that is downloadable to a mobile device, which prominently displays a brand identity, often via the name of the app and the appearance of a brand logo or icon, throughout the customer experience'* (McLean *et al.*, 2019). Unlike E-Commerce websites or web apps (responsive web pages created for mobile browsers), native mobile apps are installed on a user's device. Running on the device itself enables native apps to avail its hardware and software components such as camera, GPS functionality, fingerprint scanners and push notifications (McLean *et al.*, 2019). While this facilitates enhanced marketing capabilities such as geo-marketing, ubiquity, personalization, gamification, incentivization (Kim *et al.*, 2016; Hsu and Chen, 2018), existing research demonstrates that user acquisition and retention still remain challenging due to the extreme competitive landscape (Antwi, 2021; Lim *et al.*, 2021).

1.1.2. Pureplay Multibrand Fashion Apps

This study defines a pureplay multibrand fashion app as *a mobile application used by online fashion retailers to sell products from multiple brands under one umbrella store*, for example ASOS and ZALANDO (Desmichela and Kocher, 2020). In fashion retail, multi-brand retailers can be further classified into omnichannel department stores such as Macy's, Selfridge's, and Bergdorf Goodman, and pureplay e-tailers like ASOS and Net-a-Porter. Unlike their omnichannel counterparts, pureplay retailers lack physical stores as a touchpoint and therefore rely solely on their website and apps as the major sales channels (Varley *et al.*, 2019).

Projected to reach USD 7.9 billion in 2025 (Euromonitor, 2021a), the U.A.E's E-Commerce market consists of several pureplay multibrand e-tailers like NAMSHI, 6th Street, Noon, etc. (discussed in section 1.2). This presents an opportunity to test a consistently understudied geography in the context of fashion marketing. In terms of market segment, this study investigates only *high street* multibrand fashion apps in the region (Namshi, 6th Street, Noon, Styli, and Sivvi) , as consumer behaviour on luxury apps (like Ounass and Farfetch) is likely to differ significantly and would therefore potentially alter the findings of the present study (Desmichela and Kocher, 2020).

1.1.3. Agile Marketing

Agile Marketing is one of the five pieces that make up Marketing 5.0; (the others being Data-driven Marketing, Predictive Marketing, Contextual Marketing, and Augmented Marketing) (Kotler, Kartajaya and Setiawan, 2021). Defined as '*the use of decentralized, cross-functional teams to conceptualize, design, develop, design, and validate products and marketing campaigns rapidly*' (Kotler, Kartajaya and Setiawan, 2021), agile marketing draws inspiration from agile software development and essentially revolves around being able to swiftly respond to market volatility and constantly changing consumer needs (Ewel, 2020). For example, ZARA's go-to-market approach based on real-time analytics, decentralized teams, concurrent processes, flexible channels, and rapid experimentation are all trademarks of an agile strategy producing 10,000 + designs per year (Kotler, Kartajaya and Setiawan, 2021). While recent studies (see Table 3.) have explored various factors to *qualitatively* characterize Agile Marketing Capabilities (AMC's), this research aims to operationalize Agile Marketing using various dimensions and *quantitatively* examine their effectiveness as a precursors to consumer's repurchase intentions.

1.1.4. Repurchase Intentions

As stated by Kotler *et al.* (2008), it costs businesses 'five to ten times more to acquire a new customer than to retain an existing one'. Apart from convincing consumers to devote limited space on their device for an app for every brand, fashion marketers are also tasked with ensuring users retain those apps accompanied by regular updates, long enough to extract a customer lifetime value higher than costs of acquisition (Antwi, 2021; Lim *et al.*, 2021). While industry practices rely primarily on discounting as an effective user acquisition strategy, this study builds on relatively limited literature in the domain of user retention strategies (Lim *et al.*, 2021). To do so, the research investigates consumer's repurchase intentions arising from agile factors that motivate consumers to engage in repeat purchases from the same retailer's app.

1.2. Rationale

According to a report by eMarketer (2018) and Adjust (2018), based on eight billion apps installs analyzed globally, users are likely to delete apps within six days on an average from the last session. E-commerce apps in particular tend to be deleted within just under 11 days from when they were last used (Adjust, 2018). Moreover in 2019, only 25% of apps downloaded were used more than once (Statista, 2021). In line with these figures, researchers have already been transitioning from preliminary studies in E-Commerce technology acceptance (Davis, 1989) essential for user acquisition, to investigating usage continuance/ user retention (Bhattacherjee, 2001; Venkatesh *et al.*, 2003; Groß, 2016). However, research concerning antecedents of M-Commerce continuance in particular, is still in its nascent stages (McLean *et al.*, 2019; Lim *et al.*, 2021). The limitations of such research further articulate insufficient validity in sectors and geographies other than the ones these studies have been conducted in. Therefore, this study aims to examine antecedents of M-Commerce continuance by studying consumer's repurchase intentions in the context of pureplay multibrand fashion apps in U.A.E.

Based on Gillespie *et al.'s* (1999) initial characterization of user retention in the form of 'website stickiness', Kim *et al.* (2016) define app stickiness as 'the degree to which consumers are willing to continue using a particular mobile app'. Extant literature on consumer behaviour in retail apps examines the effectiveness of factors such as design, personalization, informativeness, gamification as precursors of continued app usage or app stickiness (Hsieh, Lee and Tseng, 2021). However hardly any previous studies focus on the role of AMCs as a driving factor of app stickiness. The novelty of this study therefore lies in examining the effectiveness of an app's agility on consumer's repurchase intentions.

Despite their merit in driving marketing performance, AMCs have often been overlooked in academic research from a consumer perspective (Hagen, Zucchella and Ghauri, 2019; Moi and Cabiddu, 2020)**.** Although such exploratory studies provide depth of research in their managerial niche, limitations concerning purposive sampling with single case study methods (Moi and Cabiddu, 2020) and relatively narrow cohorts (specific to entrepreneurial cohorts) (Hagen, Zucchella and Ghauri, 2019) suggest the need to examine AMCs deductively by testing propositions in suitable contexts. Multibrand fashion apps struggling to differentiate themselves in a highly volatile and competitive landscape, provide an ideal context to examine the role of agility in driving desirable consumer behaviour, such as repurchase intentions (Euromonitor, 2021a).

Previous research on app marketing originating from emerging countries such as India, UK, Ghana, and China, though valid locally may lack sufficient validity and generalizability on a global scale (Ali and Bhasin, 2019; McLean *et al.*, 2019; Antwi, 2021; De Canio, Fuentes-Blasco and Martinelli, 2021). Despite a high internet penetration rate of 99.15% (The World Bank, 2019) and about two-thirds of mobile phone users shopping once or more than once a month using their devices (Euromonitor, 2020), the U.A.E remains a vastly understudied region in the context of online fashion retail. With U.A.E's M-Commerce alone expected to reach USD 3.8 billion by 2025 (Euromonitor, 2021b), such a consumer behaviour study focused on local pureplay multibrand apps like 6th Street, Namshi, Noon, Sivvi, etc., could provide rich managerial insights for regional fashion app marketers. The following table illustrates the various shopping apps featured on the U.A. E's top 25 shopping apps chart for iOS and Android app stores.

Table 1: Top 25 shopping apps on iOS and Android platforms in the U.A.E.
Secondary data compiled by author (Top Charts Explorer 42 Matters, 2021).

App	iOS App Store Rank	Google Play store Rank	Multibrand	Single brand	Pureplay	Marketplace
6th Street	**14**	**16**	✓		✓	
adidas		9		✓		
Amazon Shopping	1	1				✓
Centrepoint Online	25	15	✓			
Chicpoint	8	10		✓	✓	
DODUae		13		✓	✓	
HnM	9	18		✓		
Level Shoes	5		✓			
Max Fashion	4	6		✓		
Namshi	**15**	**17**	✓		✓	
Noon Shopping	**2**	**2**	✓		✓	✓
OUNASS Luxury Shopping	23		✓		✓	
SHEIN	3	5		✓	✓	
SIVVI Online Shopping	**21**		✓		✓	

STYLI	**6**	**24**	✓		✓
Vogacloset	18			✓	✓
ZARA	16			✓	

Table 2: Pureplay multibrand fashion apps in the U.A.E and their U.K/ EU based counterparts. 'No. Brands Retailed' data reported from Edited Market Analytics (2021).

Pureplay Multibrand Fashion Apps relevant to this study (from U.A.E)	Fashion Market Segment(s)	No. Brands Retailed	U.K/ EU equivalent
NAMSHI	High Street, Fast Fashion	742	ASOS, Zalando
Noon Shopping	High Street, Fast Fashion	570	ASOS, Zalando
6th Street	High Street, Fast Fashion	325	ASOS, Zalando
Sivvi	High Street, Fast Fashion	447	ASOS, Zalando
Styli	High Street, Fast Fashion	20	ASOS, Zalando

The study particularly focuses on U.A.E based males and females from the Gen Z (ages 18-24) and Younger Millennial (ages 25-29, 30-34) cohort who have purchased more than once from a local pureplay multi-brand fashion app, as these form the core fashion consumers highly likely to have engaged with mobile shopping (Euromonitor, 2020).

1.3. Aims and Objectives

1.3.1. Aim

To critically examine the combined effects of AMCs of pureplay multibrand fashion apps and consumers' affective states on the repurchase intentions of Gen Zs and younger Millennial consumers in the U.A.E, in order to develop a conceptual model and provide strategic recommendations for fashion app marketers to optimize user retention.

1.3.2. Objectives

1. Critically review existing literature to operationalize AMCs in the context of pureplay multibrand fashion apps.
2. Examine the impact of AMCs on consumers' affective states.
3. Investigate role of affective states – pleasure, arousal, and dominance in driving repurchase intentions.
4. Develop a conceptual model which demonstrates the combined effect of AMCs and affective states on consumers' repurchase intentions.
5. Propose suitable managerial implications for fashion app marketers to optimize user retention.

1.4. Intended Theoretical and Managerial Contribution

This study aims to build on three key areas of extant literature namely – Environmental Psychology, Agile Marketing, and Mobile App Continuance – particularly in the domain of pureplay multibrand fashion apps in the U.A.E. Theoretically, the research mainly draws on the S-O-R framework from Mehrabian and Russell's (1974) work on environmental psychology to assess the interaction between AMCs and consumers' emotional states, in order to drive repeat purchases on pureplay fashion apps.

While existing app marketing literature examines several environmental cues as precursors of desired consumer behavior, to the best of the author's knowledge, this is one of the first studies which attempts to investigate AMCs as an environmental stimuli. In doing so, the study intends to contribute empirical findings from a consumer perspective to a topic that has largely been explored from a qualitative, organizational perspective (Hagen, Zucchella and Ghauri, 2019; Moi and Cabiddu, 2020). In addition, most existing studies have investigated the effectiveness of various online marketing stimuli in a variety of settings including general E-commerce, tourism, consumer electronics, finance, online bookstores, retailer websites, and single branded fashion apps (Hsu and Chen, 2018; Ali and Bhasin, 2019; McLean *et al.*, 2019; Antwi, 2021). However, no such studies have specifically looked at the context of pureplay multibrand fashion apps. Although such apps and websites have some similarities, the effects of app marketing stimuli in a pureplay multibrand context are likely to reveal potential differences (Desmichela and Kocher, 2020). Therefore, this study attempts to contribute to the domain of consumer behaviour and psychology in m-commerce environments, by developing a conceptual model specifically tailored to the surroundings of pureplay multibrand fashion apps. Moreover, since previous work on app marketing has been limited to certain geographies, this study aims to build reliability by contributing findings from the Middle East (U.A.E), as the region has been consistently overlooked from such literature.

From an industrial standpoint, online shopping environments come with ease of price search resulting in higher switching intentions and hence, lesser repeats (Lee, 2015). Therefore, apart from its theoretical contribution, this study aims to support fashion app marketers and app developers in optimizing user retention by offering recommendations to strategically incorporate appropriate AMCs.

1.5. Overview of Research Design

This study was designed using the principles of positivism (Saunders *et al.*, 2019). A deductive explanatory approach was adopted to develop hypotheses based on secondary literature review. The primary research was based on a cross sectional, mono-method, survey strategy (Saunders *et al.*, 2019). Data was collected using an online questionnaire. This was followed by a descriptive analysis using SPSS. The main findings, were inferred via hypotheses testing using Partial Least Squares – Structural Equation Modeling (PLS – SEM) on the Smart PLS software (Hair *et al.*, 2014).

1.6. Overview of Structure

The research begins with an introduction to the context and rationale of the topic, accompanied by an outline of the overarching aim and specific objectives of the study. This is followed by a comprehensive review of extant literature, which lays the foundation to propose hypotheses and build a conceptual model specifically for the domain of fashion apps and agile marketing. A section on research design then discusses the underlying philosophy, methodology, and research instrument at length. Following this, the analysis and findings provide a detailed statistical examination of the data collected, including validation of the proposed hypotheses, refitting of the conceptual model, and some supplementary statistical tests. The study then discusses the findings by relating them to existing literature and generating practical implications for industry professionals.

Chapter Two LITERATURE REVIEW

2. Literature Review

2.1. Theoretical Background

2.1.1. The Environmental Psychology of Multibrand Fashion Apps

Rooted in environmental psychology, Mehrabian and Russell's (1974) Stimulus-Organism-Response (S-O-R) Model proposes that an individual's behavioral *response* to external environmental cues (*stimuli*) is facilitated by internal *organism states*.

Although seminal in nature, the model has been applied extensively in modern retail literature to study the effect of sensory and cognitive environmental cues on consumer behaviour such as fashion purchase intentions in both online and offline contexts (Watson, Alexander and Salavati, 2020; Tseng, Hsieh and Lee, 2021; Wadera and Sharma, 2019). Amongst its recent applications in digital environments, the model was used as an overarching foundation in the context of gamified shopping apps like Starbucks, McDonald's, MUJI, and Nike to examine the effects of gamified marketing strategies (Hsieh, Lee and Tseng, 2021; Tseng, Hsieh and Lee, 2021), and also as an underpinning theory to investigate effects of augmented reality solutions (Watson, Alexander and Salavati, 2020).

Limitations of such aforementioned studies, however, accentuate two major opportunities for further research. First, is the need to examine the effectiveness of the S-O-R framework in other digital environments, and second, is the need to validate the effectiveness of the model with different types of stimuli. As demonstrated in literature, pureplay multibrand shopping environments differ significantly from their single brand counterparts (Desmichela and Kocher, 2020). For example, rational (vs. intuitive) thought processes are accelerated as consumers move from in-store to online, and from single brand to multi-brand shopping with decreasing levels of hedonism in the shopping environment (Desmichela and Kocher, 2020). Thus, the present study aims to address the first scholarly limitation articulated earlier, by attempting to validate the S-O-R framework in a pureplay multibrand setting where its implications haven't been investigated before. In addition, while most of the marketing studies based on S-O-R have assessed different types of marketing strategies such as gamification or augmented reality as an external stimuli (Watson, Alexander and Salavati, 2020; Hsieh, Lee and Tseng, 2021), to the best of the author's knowledge, none have previously examined agile marketing. Thus, this research also addresses the second limitation by seeking to validate the S-O-R framework using AMCs as a novel stimuli.

As asserted by Mehrabian and Russell (1974), the process of eliciting a behavioral outcome from an external stimulus is facilitated by the organism's internal emotional states classified as pleasure, arousal, and dominance (PAD) (Hsieh, Lee and Tseng, 2021). Effectiveness of app marketing stimuli on desired consumer behaviour has previously been investigated with various mediating and moderating effects. For example, customer engagement can mediate relationships between shopping gamification and intention to buy (De Canio, Fuentes-Blasco and Martinelli, 2021), extrinsic motivators and app continuance (Tseng, Hsieh and Lee, 2021), and anthropomorphism and app continuance (Lim *et al.*, 2021); customer satisfaction can mediate the dynamic between gamification and brand love (Hsu and Chen, 2018) ; previous shopping experience can moderate the path between engagement and purchase intentions (De Canio, Fuentes-Blasco and Martinelli, 2021). However, despite the significance of emotional factors, research demonstrating their mediating effects on desirable consumer behaviour is relatively underdeveloped (Hsieh, Lee and Tseng, 2021). Hence, this study builds on foundations of environmental psychology using Mehrabian and Russell's (1974) Pleasure-Arousal-Dominance (PAD) model, to examine the mediating role of dimensions of consumer psychology in driving consumer's repurchase intentions.

2.1.2. AMCs as Environmental Stimuli

Drawing from a combination of agile software development and lean start up methodologies, agile marketing was initially conceptualized as the Agile Marketing Manifesto in June 2012 (Ewel, 2020). Formally defined by the pillars in its manifesto (see appendix A 3.1.), in essence agile marketing is about swiftly creating and delivering value in response to the rapidly changing consumer demands, market dynamics, and competitive landscape (Hagen, Zucchella and Ghauri, 2019; Moi and Cabiddu, 2020). For the purpose of this research AMCs shall be defined in line with Guo et al. (2018), as '*the extensible ability to proactively sense and act on market signals, continuously learn from market experiments, and integrate and coordinate social network resources to adapt to market changes and predict industry trends*' (Moi and Cabiddu, 2020).

Despite its merits in achieving depth of research for a particular niche, literature surrounding agility in the marketing domain however, is limited to exploratory inductive approaches, possibly due to the novelty of this research area (Hagen, Zucchella and Ghauri, 2019; Moi and Cabiddu, 2020). For example, while Moi and Cabiddu (2020) present a theoretically sound AMC framework identifying four broader agile capabilities (adaptability, collaboration, continual innovation, and forecasting), their findings are limited to a single case study about a digital home-rental business with no direct link to fashion. Hagen, Zucchella and Ghauri (2019) too, provide a comprehensive theoretical framework highlighting flexibility and selective responsiveness as two major agile business practices. However, despite considering a greater number of cases (three digital start-ups) and an additional non-digital business to enhance generalizability, three out of the four firms chosen, come from Italian origins with limited international exposure and hence limited reliability. Moreover, none of the cases selected show a direct association with fashion (Hagen, Zucchella and Ghauri, 2019). While the purposive sampling undertaken in both the aforementioned studies seems likely to have enhanced credibility through a selection of highly relevant, agile-centric firms, it may have potentially resulted in some form of researcher bias (Bryman and Bell, 2011). Thus, the present research aims to build on the depth of findings from such studies and enhance their reliability by investigating AMCs in different industrial and geographical contexts using a quantitative approach with zero to minimal researcher bias. In addition, the present study also delivers the much required and previously unexamined consumer perspective on marketing agility (Hagen, Zucchella and Ghauri, 2019; Moi and Cabiddu, 2020).

The pureplay multibrand fashion domain of this study provides a suitable background to empirically operationalize and test the effectiveness of AMCs in eliciting desirable consumer responses, since core fashion consumers are demanding 'always-on brands' to attend to their needs 24/7 (Kotler, Kartajaya and Setiawan, 2021). Based on the qualitative characterization of agile marketing (Table 3.), and antecedents of app usage continuance identified in extant literature (Table 4.), this research operationalizes the environmental stimuli of AMCs in multibrand fashion apps using five dimensions namely – *Newness of Assortment, Transparent User Experience, Ubiquity, Personalization, and After-Sales Service* (further discussed in section 2.2). Since each of these lower order dimensions have been empirically tested in previous findings (Hsieh, Lee and Tseng, 2021; Lim *et al.*, 2021), their adaptation can contribute towards enhancing the reliability of this research and also test their validity in a different context.

Table 3: Characterization of Agile Market from extant literature. "Customer Centric Elements" discussed in the last column refer to dimensions of agile marketing that could be quantified from a consumer perspective for this study.

Authors	Characterization of Agile Marketing	Customer Centric Elements (Relevant for this study)
Ewel, J. (2020)	**The Six Disciplines of Agile Marketing**	
	• Alignment – Aligning marketing goals with the rest of the business goals and customer expectations	
	• Structure – Collaborative, cross functional teams	
	• Process Management – Applying process like Scrum and Kanban to manage marketing	
	• Validated learning – Practicing rapid iteration, testing, and multiple experiments to constantly learn from data	
	• **Adapting to change –** Adapting to changes in marketplace, competitive landscape, consumer behaviour. Responding to disasters and opportunities.	✓
	• **Creating remarkable consumer experiences –** Consumer experience is the 'ultimate outcome' which lies at the 'heart of agile marketing'.	✓
Kotler, P., Kartajaya, H. and Setiawan, I. (2021)	**Key Components for Developing Agile Marketing**	
	• Real time analytics capabilities- capture customer data to monitor changes in real time.	
	• Decentralized teams – multiple, small, cross functional teams assigned to specific timeboxed tasks.	
	• **Flexible product platform –** products that are well integrated and continuously upgraded, with each iteration delivering a usable output equipped with customization capabilities.	✓
	• Concurrent Process- different stages of a marketing plan run in parallel as opposed to running sequentially.	
	• Rapid Experimentation – Instead of pre-launch testing, Minimum Viable Products (MVPs) are sold to real customers in line with lean start up methodologies.	
	• **Open Innovation –** leverage internal and external opportunities for innovation such as customer co-creation and third party collaboration.	✓
Moi, Cabiddu (2020)	**The Agile Marketing Capability Framework**	
	• **Adaptability and flexibility towards changing customer needs and international settings.**	✓
	• Integrated teams working in collaborative environments	
	• **Continual, fast-paced innovation**	✓
	• **Forecasting and monitoring** needs of the market by anticipating and fulfilling customer expectations	✓
Hagen, Zucchella, Ghauri (2018)	**Reconceptualization of Strategic Agility (driven by Marketing)**	
	• **Flexibility** - Being flexible enough to respond with speed and save time with respect to customer demands, stakeholder requirements, and management of resources.	✓
	• **Selective Responsiveness** – Create value by responding to customer's hidden and unsatisfied requirements. Undertake experimentation to test innovative opportunities in business development	✓

2.1.3. Continuity of Fashion Apps: Repurchase Intentions

While some previous studies contextualize app usage continuance in the form of 'continued usage intention' (Hsieh, Lee and Tseng, 2021) or 'app continuance' (Tseng, Hsieh and Lee, 2021), for the purpose of this research continuance shall be represented by consumer's 'repurchase intentions' (Antwi 2021; Ali and Bhasin, 2019; Chiu et al., 2014; Liang, Choi and Joppe, 2018). This is because, in addition to other reasons for continued app usage (like browsing and price comparison), repurchase intentions encapsulate a transactional element critical to sustaining the business of multi brand fashion apps.

According to Bhattacherjee (2001), factors driving continued usage of a technological system (in this case multi brand fashion apps) differ from factors driving its initial adoption. Continuity in consumer behaviour is influenced by the extent of user's confirmation towards an initial expectation from the service, the perceived usefulness (i.e., level of expectation formed after initial acceptance) of the technology after, and satisfaction with previous experience of using the technology. In line with Bhattacherjee's (2001), Expectancy Confirmation Model, McLean *et al.* (2019) affirm that although models based on technology acceptance (Davis, 1989) are relevant in the initial adoption phase, the strength of variables influencing the initial acceptance of mobile applications like perceived ease of use, perceived usefulness, customization, and enjoyment, differs significantly with an app's continued usage. This also aligns with previous research (Venkatesh *et al.*, 2003; Groß, 2016) which suggests that the factors influencing the primary acceptance of technology are likely to vary in level of importance across its continued acceptance as consumers' perceptions about a product/ service shift from external sources of information to their own experience of using it.

However, despite its merits in understanding continuance intention, research on technology continuance, often neglects the effect of consumer's intrinsic motivations (with the exception of customer satisfaction) (Kim *et al.*, 2014; Wu, Liu and Cui, 2021). In doing so, it neglects other findings which in fact, highlight the significance of factors such as user engagement (De Canio, Fuentes-Blasco and Martinelli, 2021; Tseng, Hsieh and Lee, 2021) and hedonistic patterns of consumption (Hsu and Chen, 2018), in driving desirable consumer behaviour. Therefore, by employing the PAD model (Mehrabian and Russell, 1974), this study includes an emotional aspect for studying app usage continuance to address limitations regarding neglect of intrinsic motivation articulated in academia.

Table 2. provides an overview of the reviewed literature to illustrate the antecedents and mechanism of desired consumer behaviour (outcome) examined in various E-Commerce and M-commerce domains. It also illustrates the research gap (multibrand fashion apps and agile marketing) which the present study aims to bridge.

Table 4: Summary of the literature reviewed, explaining the various antecedents, mechanisms, and outcomes of consumer behaviour on mobile apps or E-Commerce platforms. All data has been sourced and complied by the author. Last two columns specifically indicate the research gaps in the context of pureplay multibrand fashion apps and AMCs as relevant for this study.

Author	Antecedents	Mechanism	Outcome	Context	Theory	Findings	Multibrand Fashion App Context?	Potential AMC Dimensions
Present Study	**Agile Marketing Capabilities**	**Pleasure, Arousal, Dominance**	**Repurchase Intentions**	**Multibrand Fashion apps in U.A.E**	**Environmental Psychology consisting of S-O-R and PAD Framework** (Mehrabian and Russell, 1974)		**Yes**	**Newness of Assortment, Transparent UX, Ubiquity, Personalization, and After Sales Service**
(Ali and Bhasin, 2019)	Perceived Price, Delivery Quality,	Customer Satisfaction, Perceived Value	Repurchase Intention	General E-Commerce in India	Information Systems Success Model (DeLone and McLean, 1992), Belief-Attitude-Behaviour Model and TAM (Davis, 1989; Davis, Bagozzi and Warshaw P., 1989)	Price and Delivery Quality had significant effect on Perceived Value, but not on Customer Satisfaction. Perceived value had significant effects on Repurchase intention directly and through Customer Satisfaction.	No	Delivery Quality
(Antwi, 2021)	Customer Trust, Customer Commitment, Customer Satisfaction	Price Level	Repurchase Intention	Online retailers in Ghana	Relationship Marketing	Customer trust positively affects repurchase intentions and price level. Customer commitment has a significant positive effect on price level and repurchase intentions. Customer Satisfaction had significant positive effect on Price Level but not on Repurchase Intentions.	No	None

(Chiu *et al.*, 2014)	Utilitarian Benefits, Hedonic Benefits	Utilitarian Value, Hedonic Value, Perceived Risk	Repeat Purchase Intention	Yahoo! Kimo E-Commerce store in Taiwan	MEC (Gutman, 1997), Prospect theory (Kahneman and Tversky, 1979)	Utilitarian value is a stronger predictor of repeat purchase intentions than hedonic value. Perceive risk as a weak negative effect on repeat purchases. Perceived risk negatively moderates effect of utilitarian value and positively moderates the effect of hedonistic value (so they need to be aroused) on repeat purchases.	No	Utilitarian benefits
(McLean *et al.*, 2019)	Perceived ease of use (EOU), Perceived Usefulness, Enjoyment, Subjective Norm, Customizatio n	Attitude towards m-commerce app, Attitude towards the brand, Loyalty towards the brand, Screen Size	Purchase Frequenc y	Apparel m-commerce apps in UK	Expectancy Confirmation Theory of Information Technology (Bhattacherjee, 2001)	Following initial adoption, Customization, Enjoyment, Perceived EOU, and Perceived usefulness influence attitude towards the app with continued usage. Subjective norms do not affect attitude towards app with usage continuance. Attitude towards the brand influences Loyalty, attitude towards brand and Purchase Frequencies with continued usage. Attitude towards brand, and purchase frequencies are not affected during initial adoption phases.	Yes (Partially)	Customizatio n
(Hsieh, Lee and Tseng, 2021)	Ubiquity, Personalizati on, Informativen ess, Entertainme nt, Aesthetic Design, Gamification	Dominance, Pleasure, A*rous*al	Continuou s Usage Intention, Brand Loyalty	Gamified apps: Starbucks, Nike (Nike Run), Under Armour (My Fitness Pal)	S-O-R and PAD Models (Mehrabian and Russell, 1974)	All three emotional factors- P, A and D influence brand loyalty and continuance intention. Dominance is driven by Ubiquity, Personalization, and informativeness, Pleasure by Aesthetics and Entertainment, and Arousal by Gamification.	No	Ubiquity, Personalizati on, Informativene ss
(De Canio, Fuentes -Blasco and Martinel li, 2021)	Shopping Gamification, Focused Attention, Shopping Enjoyment, Socialness	Shopping Engagement , Previous Shopping Experience	Intention to buy	WeChat app in China	Technology Acceptance Model (TAM) (Davis, 1989), Theory of Reasoned Action (Fishbein and Ajzen, 1980)	Shopping Gamification, Focused Attention, Shopping Enjoyment, Socialness positively effect Engagement. Shopping Engagement and Previous shopping experience affects Intentions to buy. Previous shopping experience also moderates engagement and intention to buy pathway.	Yes	None
(Lim *et al.*, 2021)	Anthropomor phism Presence (AP) and Marketing Mix (higher order constructs)	Customer Engagement (CE), Prevention Focus, Promotion focus	Continuan ce Use Intention	Millennial Retail app (Shopee, Taobao, Lazada, Uniqlo, HnM, etc.) shoppers in Malaysia	Two factor theory (Herzberg, 1987), Regulatory Focus Theory (Higgins, 1998)	AP did not affect continuance directly but indirectly via Customer engagement. MM influence app continuance. CE was the strongest predictor of continuance. AP is stronger predictor of CE than MM. CE Mediates the relation between MM, AP and Continuance. MM-CE path is stronger for	Yes (Partially)	Product Assortment, Transparency , Aftersales Service

						prevention-focused consumers.		
(Hsu and Chen, 2018)	Experience of Gamification of Marketing Activities (GMAs)	Hedonic value (HV), Utilitarian value (UV), Satisfaction, Brand Love	Brand Loyalty, Positive WoM, Resistance to negative information	Online bookstore in Taiwan	Technology acceptance (Davis, 1989), Continuous Usage Intentions (Bhattacherjee, 2001), Hedonic and Utilitarian Patterns of Consumption.	Experience of GMAs positively affects HV and UV. HV and UV have a significant positive effect on Customer satisfaction-after sales UV will dive Satisfaction and Brand love. Brand love drives loyalty, Positive WoM and Resistance to negative information.	No	Utilitarian Value
(Tseng, Hsieh and Lee, 2021)	Symbolic benefits, Incentive provision, Goal Clarity, Design Aesthetics, Playability	Consumer Brand Engagement - Cognition, Affection, Activation	App Continuance Intention, Purchase Intention, Brand Loyalty	Multiple gamified apps: McDonald's, MUJI, Starbucks, Nike, Family Mart, 7-11, Eslite, O-Bank	S-O-R (Mehrabian and Russell, 1974), Elemental Tetrad Model (Schell, 2008)	Symbolic benefits, Incentive provision, Goal Clarity, Design Aesthetics, and Playability drive Consumer brand Engagement which in turn facilitates App Continuance Intention, Purchase Intention and Brand Loyalty	No	None
(Kim *et al.*, 2016)	Perceived ubiquity, Informativeness, Personalization	Perceived Usefulness, Engagement	Mobile App Stickiness, WOM	Gamified food and shopping Apps	Technology Acceptance Model (TAM) (Davis, Bagozzi and Warshaw P., 1989)	App stickiness is influenced by app usefulness and app engagement. Usefulness is influenced by ubiquity, informativeness, and personalization.	No	Ubiquity

2.2. Hypothesis Development

2.2.1. Operationalization of AMCs

Since AMCs are a relatively abstract concept, it may not be justified to measure them with a definite set of indicators (Bryman and Bell, 2011). As illustrated in previous exploratory studies (Table 3.), AMCs may comprise of various dimensions depending on the context they are being evaluated in. Each of these aspects or dimensions can then be measured using a set of indicators available from literature or designed based on theory (Bryman and Bell, 2011). Building on the qualitative characterization of AMCs in extant literature and previously tested precursors of app continuance and/or repurchase intentions (Tables 3 and 4.), this study operationalizes AMCs as a multidimensional concept comprising of the following five aspects:

i. ***Newness of Assortment:*** The fashion industry by nature is characterized by changing trends. Therefore, the ability to forecast (Moi and Cabiddu, 2020), and turnover maximum designs in a limited profit timeline, reflects a multibrand app's agility towards changing consumer tastes and requirements (Kotler, Kartajaya and Setiawan, 2021). With several pure players competing for market share by selling similar high street brands and product lines, newness of assortment can enable multi brand apps to stand out and stay ahead of the curve. Adapted from Lim *et. al'*s (Lim *et al.*, 2021) 'assortment' construct, 'newness of assortment' denotes a multibrand app's variety of inventory in terms of new brands, trendy product lines, and inclusion of new colors, sizes, and styles.

ii. ***Transparent User Experience:*** As stated by Ewele (2020), customer experience lies at the heart of agile marketing. In line with this, findings from Hsieh, Lee and Tseng (2021) and Lim et. al (2021) also affirm the significance of app marketing stimuli such as 'informativeness' and 'channel transparency' in creating an effective shopping experience. Based on these two constructs, 'transparent user experience' signals a multi brand app's ability to constantly update the consumers with latest real time analytics at every stage in the consumer journey – such as accurate descriptions before purchase and order tracking at every stage of delivery.

iii. ***Ubiquity:*** Agile brands are those which are able to swiftly cater to their consumer's demands 24/7 (Kotler, Kartajaya and Setiawan, 2021). By living on a user's device, the ubiquitous nature of m-commerce enables multibrand apps to achieve such agility with the help of flexible product platforms (mobile apps) capable of attending to the consumer's needs anytime, anywhere (Kim *et al.*, 2016; Hsieh, Lee and Tseng, 2021). Therefore, in terms of an app's agility, ubiquity signifies its ability to grant users the access to products and services anytime, anywhere.

iv. ***Personalization:*** One of the chief characteristics of agile marketing is the ability to monitor user preferences and translate real time analytics into value creation for the consumer (Ewel, 2020; Moi and Cabiddu, 2020). Personalization tactics such as remarketing ads based on products in a user's wish list, or tailored emails based on user's purchase history enable value creation by staying on top of customer preferences (McLean *et al.*, 2019; Hsieh, Lee and Tseng, 2021), and therefore demonstrate an app's agility towards sensing and predicting consumer behaviour.

v. ***After-Sales Service:*** In line with Hagen *et. al's* (2019) findings, flexibility and responsiveness surface as critical factors for agility. Within the domain of multi brand fashion apps, these factors can be extrapolated to the apps' after sales service (Lim *et al.*, 2021). In order to reflect agile capabilities, an app's after-sales service needs to be characterized by speed, flexibility, and efficiency . Therefore, fashion marketers can impart agility to their mobile platforms by increasing 'flexibility and selective responsiveness' towards various after-sales queries such returns, refunds, and exchanges (Hagen, Zucchella and Ghauri, 2019).

Using the five dimensions discussed above this study hypothesizes the existence of relationships between the various AMCs, consumer's organism states, and repurchase intentions using the S-O-R framework as the overarching theory.

2.2.2. Antecedents of Pleasure, Arousal, and Dominance

2.2.2.1. Antecedents of Arousal

In environmental psychology, arousal is predominantly associated with feelings of excitement, alertness, or activation, upon being stimulated by any external factor(s) (Mehrabian and Russell, 1974; Hsieh, Lee and Tseng, 2021). Existing literature examines antecedents of arousal directly and indirectly. For example, while Hsieh, Lee and Tseng (2021) observe the effects of branded app atmospherics directly on the arousal construct, other studies examine the role of app marketing elements on the construct of consumer engagement. In case of the latter, consumer engagement can be linked to arousal by drawing a parallel between the stimulating aspects of both these constructs. Therefore, considering the correlations between assortment and consumer engagement, and between personalization and arousal, established in previous literature (see Table 4.), this study proposes the existence of a positive impact of two AMCs- newness of assortment and personalization, on arousal.

Newness of Assortment and Arousal

Research suggests that fashion consumers feel engaged and excited by the depth and variety of product offerings in an app's marketing mix (Lim *et al.*, 2021). Shoppers are also attracted by the 'trending' factor, especially in a digital context where new trends are made available every day on their fingertips (Djafarova and Bowes, 2021). Being stimulated by newness of assortment can also be viewed as a form of hedonic value and shopping enjoyment both of which have a positive effect on repeat purchases (Chiu *et al.*, 2014; McLean *et al.*, 2019).Therefore, considering the agile aspect of trendiness and the previously confirmed effects of marketing mix on engagement, (which in turn drives app continuance) this study hypothesizes the following:

H1: Newness of assortment is positively associated with feelings of arousal.

Personalization and Arousal

Hsieh, Lee and Tseng (2021) affirm that personalization indirectly influences continuance usage intentions of gamified apps. This aligns with findings from other studies which illustrate positive correlations between similar constructs such as customization (McLean *et al.*, 2019), perceived personalization (Kim *et al.*, 2016), anthropomorphism (Lim *et al.*, 2021), and repeat purchases. However, while Hsieh, Lee and Tseng (2021) examine the mediating role of dominance, Kim *et al.* (2016) and Lim *et al.* (2021) postulate customer engagement as the intermediary facilitating the outcomes from personalized activities. Although appropriate in Hsieh, Lee and Tseng *'s* (2021) context of gamification , where personalization can indeed establish a greater sense of control, this might differ in the case of multibrand fashion apps. Considering the agility of such apps, personalization via remarketing ads, push notifications and recommendations based on purchase history, happens mostly outside the user's control. Although it is up to the user to opt-in for such tactics, once opted for, personalization agility is more about stimulating attention (arousal) than activating sense of control. (The control in fact lies in hands of marketers who decide on the medium and time which will most excite a consumer for personalized push). Hence, this study proposes that personalization in multibrand apps is linked more with arousal (than dominance), as suggested by Kim *et al.* (2016) and Lim *et al.* (2021). This leads to the following hypothesis:

H2: Personalization is positively associated with feelings of arousal.

2.2.2.2. Antecedents of Dominance

The dominance aspect of the PAD model signifies a 'sense of control' within the consumer's mindset (Mehrabian and Russell, 1974). High levels of dominance can be considered equivalent to reduced levels of risk and uncertainty. According to Chiu et al., (2014) perceived risk *negatively* moderates the path between utilitarian benefits and repeat purchases. Therefore, *if perceived risk is low* (i.e., *dominance is high*), utilitarian features are likely to drive more purchases. Since transparency and ubiquity provide certain utilitarian benefits such as convenience and product information (Chiu *et al.*, 2014), this study proposes that dominance will facilitate the path between AMCs and repurchase intentions for Transparent User Experience and Ubiquity.

Transparent User Experience and Dominance

This study characterizes 'transparent user experience' as an app's ability to promptly provide customers with precise real time information about their purchases. According to Lim *et al*. (2021) and Ali and Bhasin (2019), channel transparency and delivery quality (encompassing timely and accurate logistics, online tracking, order changes and cancellations) have an indirect positive influence on app continuance and repurchase intentions. Considering that informativeness is a part of a channel's transparency, these findings are also in line with Hsieh, Lee and Tseng *'s* (2021) study which is one of the few to have affirmed the correlation between informativeness and dominance in the realm of app continuance. Kim *et al.* (2016) too, demonstrate the indirect effects of perceived informativeness on app stickiness. However, to qualify as agile, informativeness should be able to combine static descriptions (about products, services, promotions, etc.) with dynamic real time updates. Given the intangible nature of mobile shopping, such functional agility reduces user's perceived risk and uncertainty (Chiu *et al.*, 2014), thereby increasing control over the shopping experience (Hsieh, Lee and Tseng, 2021). Thus, this research hypothesizes the following:

H3: Transparent user experience is positively associated with feelings of dominance.

Ubiquity and Dominance

Extant literature highlights the 'anywhere, anytime' ubiquitous nature of mobile phones as one of the most significant aspects of m-commerce (Balasubramanian, Peterson and Jarvenpaa, 2002; McLean *et al.*, 2019). According to Kim *et al.* (2016), perceived ubiquity is one of the strongest precursors of app usefulness, which in turn leads to increase app stickiness. Hsieh, Lee and Tseng (2021) also conform to these findings by establishing ubiquity as an indirect predictor of app continuance, mediated by dominance. Both these studies however do not specifically examine ubiquity in the context of agility of pureplay multibrand retailers.

In terms of agile capabilities, the ubiquity of mobile apps allows pureplay multibrand retailers to be omnipresent, thereby saving time and imparting 'spatial flexibility' to the platform (Kim *et al.*, 2016; Hagen, Zucchella and Ghauri, 2019; Moi and Cabiddu, 2020). Perceived ubiquity imparts various utilitarian benefits such as 'continuity, immediacy, portability, and searchability' (Hsieh, Lee and Tseng, 2021). Considering that utilitarian benefits are likely to drive purchase frequencies when perceived risk is low (Chiu *et al.*, 2014), the ubiquitous capabilities of mobile shopping, such as geo-marketing, global shipping, and on-demand deliveries can therefore behave as environmental stimuli to minimize uncertainty and build a sense of control over one's consumer journey. Hence, this study proposes the following:

H4: Ubiquity is positively associated with feelings of dominance.

2.2.2.3. Antecedent of Pleasure

The dimension of pleasure is associated with feelings of joy, happiness, and satisfaction with the environment (Mehrabian and Russell, 1974). Fashion consumers are largely motivated by hedonistic values (Desmichela and Kocher, 2020). In app marketing too, hedonic features such as aesthetics and entertainment have been directly linked to feelings of pleasure (Hsieh, Lee and Tseng, 2021). However, other literature around retail apps articulates that in addition to hedonic values, utilitarian values too contribute to customer satisfaction (pleasure) (Parker and Wang, 2016; Hsu and Chen, 2018). This is because mobile apps have limited experiential scope, and therefore focus largely on utilitarian features to induce engagement (Parker and Wang, 2016).

After-Sales Services and Pleasure

Considering AMCs as a utilitarian environmental cue, this study proposes that agility in after-sales services is likely to induce feelings of pleasure. After-sales services can be defined as the provision of services that follows after a particular purchase from a retailer (Lim *et al.*, 2021). By ensuring timely technical support, swift replacement of unsatisfactory (e.g., damaged, defective, or incorrect) goods, post-purchase monetary services (such as refunds, returns, or exchanges), warranties, and proof of authenticity, multi brand fashion apps can cultivate a stronger bond with their consumers (Lim *et al.*, 2021). Therefore, agile after-sales services can be considered to provide utilitarian benefits which, (as discussed earlier), can in turn increase customer satisfaction and hence, pleasure (Hsu and Chen, 2018). In line with this, the study hypothesizes the following:

H5: After-sales services are positively associated with feelings of pleasure.

2.2.3. Outcome of Pleasure, Arousal, and Dominance

Consumer behaviour or ‘response’ is the final stage in the S-O-R framework. Based on the establishment of the three emotional states of PAD, an individual is likely to either continue engaging with an environment or avoid it entirely (Mehrabian and Russell, 1974).

While few studies have assessed the behaviour-determining role of *arousal* in particular, several have empirically tested the positive effect of *customer engagement* on continuity of mobile apps (Kim *et al.*, 2016; Hsieh, Lee and Tseng, 2021; Lim *et al.*, 2021; Tseng, Hsieh and Lee, 2021). In these studies, usage continuity arising from customer’s engagement has been measured using various constructs such as mobile app stickiness, app continuance intention, and continuous usage intention. If consumer’s interest is piqued by an app’s agility in terms of providing trendy assortments and personalized content/ advertisement, they may be inclined to return to an app for more purchases. Therefore, drawing a parallel between the stimulating aspects of engagement and arousal, this study proposes that arousal will contribute positively towards consumer’s repurchase intentions.

Hsieh, Lee and Tseng (2021) affirm the mediating effects of dominance in driving app continuance of gamified branded apps. However, even if an online environment is non-gamified, previous research demonstrates that having an increased sense of control can lower uncertainty and enhance satisfaction, which in turn leads to repeat purchases (Weathers, Sharma and Wood, 2007; Ali and Bhasin, 2019). In the case of pureplay fashion apps, users have no access to physical trials or sales advisors in order to make concrete decisions. Therefore, inducing a sense of control by other elements such as transparency and ubiquity, can increase consumer confidence, thereby leading to repeat purchases (Hsieh, Lee and Tseng, 2021) .

Previous studies have examined the effects of various forms of pleasure such as enjoyment, brand love, and satisfaction on consumer behaviour. For example, De Canio, Fuentes-Blasco and Martinelli (2021) affirm the role of enjoyment in driving purchase intentions, McLean *et al.*, (2019) articulate the effects of enjoyment on repurchase intentions, and Chiu *et al.* (2014) ascertain the role of brand love in driving loyalty. In terms of customer satisfaction however, while Ali and Bhasin's (2019) study asserts a positive correlation with repurchase intentions, Antwi's (2021) findings show that satisfaction doesn't significantly impact repurchase intentions. Though both studies had similar number of responses, a plausible explanation for this contradiction could be the differences in samples' geographies, use of different scales to measure satisfaction, and self-selection bias (such as non-response) which was not quantified in either of these studies. According to Hsieh, Lee and Tseng (2021), however, there exists a direct positive influence of pleasure on app continuance. This is also in line with Bhattacherjee's (2001) EC theory of IS continuance which signifies the role of satisfaction in driving continuance of information systems. Thus, this study proposes that pleasure is positively related to repurchase intentions.

Based on the above links between the emotional states of PAD and repeat purchases, this research postulates the following set of hypotheses:

H6a: Feelings of arousal have a positive influence on repurchase intentions.
H6b: Feelings of dominance have a positive influence on repurchase intentions.
H6c: Feelings of pleasure have a positive influence on repurchase intentions.

2.2.4. Proposed Conceptual Framework.

The following figure illustrates all the hypotheses developed in preceding sections in the form of a proposed conceptual model. The five variables on the left represent the various AMCs (stimuli), postulated to positively influence consumers' affective states (signified by pleasure, arousal and dominance), which in turn may impact fashion repurchase intentions (response).

It should be noted that any subsequent references made to 'exogenous' variables refer to the five AMCs (arrows going out from the construct), and any mentions about endogenous variables denote the three emotional states and repurchase intentions (arrows coming into the construct) (Hair *et al.*, 2014).

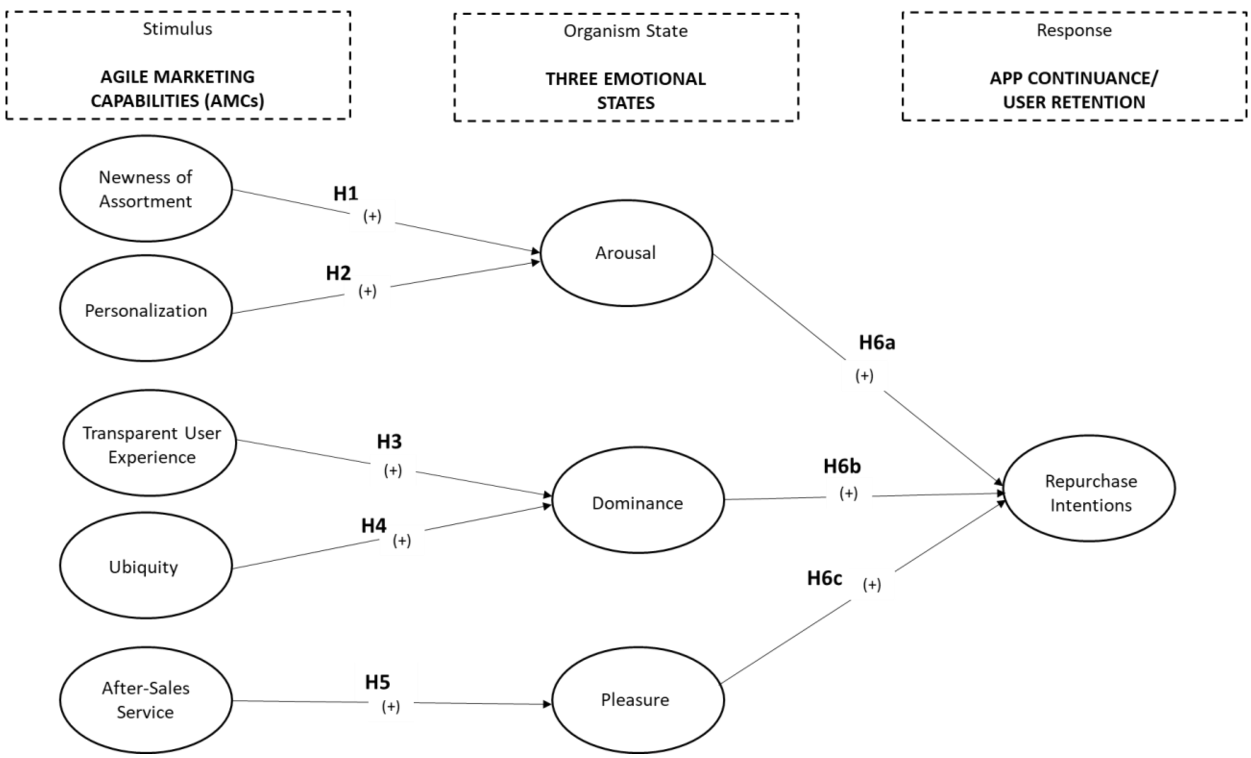

Figure 1: Proposed conceptual framework

Chapter Three RESEARCH DESIGN

3. Research Design

The purpose of this research was to generalize findings about consumer attitudes towards AMCs of multibrand fashion from a sample of a population to the population itself, in order to derive inferences about fashion repurchase intentions of the target population (Creswell, 2014). The research onion (Figure 2.) adapted from Saunders *et al.* (2019) illustrates the various stages included in the design of this study.

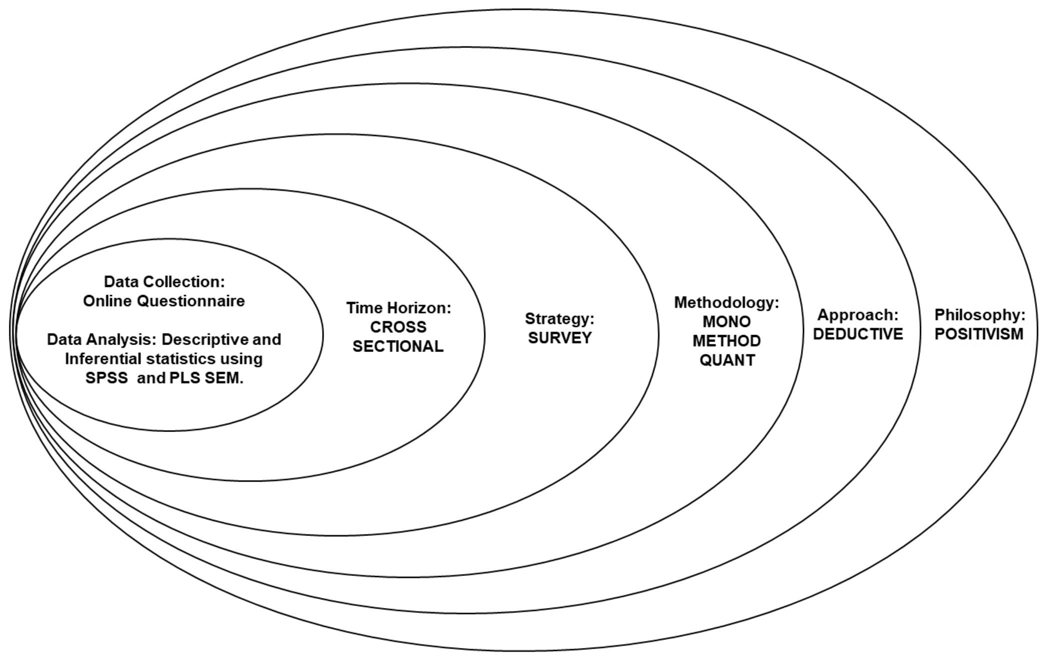

Figure 2: The Research Onion as adapted from Saunders *et al. (2019).*

3.1. Philosophical Context

Previous studies on the subject of app marketing followed highly structured and replicable methodologies, demonstrating the use of an underlying positivist philosophy (McLean *et al.*, 2019; Antwi, 2021; Lim *et al.*, 2021; Tseng, Hsieh and Lee, 2021). From a philosophical perspective this research too, was designed on the foundations of positivism. Epistemologically, positivism constitutes 'working with observable social reality' in order to test hypotheses and derive 'law like generalizations' similar to those produced by scientific research (Saunders *et al.*, 2019). Ontologically, adopting a positivist stance for this research facilitated an 'objective' study of reality. This is was advantageous since by placing the researcher external to the process of data collection, the study could generate 'value-free' findings (Saunders *et al.*, 2019).

Although a positivist approach may lack the depth of research achievable by exploratory studies, extant literature around app marketing has already theorized several models in the domain of app marketing (McLean *et al.*, 2019; Antwi, 2021; Lim *et al.*, 2021; Tseng, Hsieh and Lee, 2021). Thus, in contrast to interpretivism, adopting a positivist stance was more suitable since this study attempted to build on such existing frameworks by validating them in other contexts and geographies, as opposed to devising new theories (Saunders *et al.*, 2019). Moreover, limitations articulated in previous exploratory studies on agile marketing highlighted the need to examine AMCs from a consumer perspective using empirical evidence (Hagen, Zucchella and Ghauri, 2019; Moi and Cabiddu, 2020). Adopting a positivist stance for this study therefore provided a foundation to gather such empirical evidence in the form data collected to study consumer behaviour on multibrand fashion apps in the U.A.E.

3.2. Research Approach and Design

This research was designed deductively using a mono-method quantitative methodology. As the research objectives were explanatory (i.e., seeking to explain causal relationships between fashion app marketing and consumer behaviour) a deductive approach was selected (Saunders *et al.*, 2019). This is because unlike exploratory studies on retail apps such as that by Parker and Wang (2016), this research did not intend to build new theories but instead focused on verification or falsification of existing literature. Adopting a deductive approach facilitated the reductionist aspect of positivism, in the sense that the reviewed literature was deductively reduced into discrete variables and hypotheses (Creswell, 2014).

This approach also enabled the replication of methodologies followed in previous studies whilst also attempting to enhance the replicability of this research for future academics (Bryman and Bell, 2011). In line with replicability, a survey strategy was adopted for the data collection process as observed in previous studies (Kim et al., 2016; McLean et al., 2019; De Canio, Fuentes-Blasco and Martinelli, 2021; Hsieh, Lee and Tseng, 2021). This strategy offered several advantages including economic feasibility and rapid turnaround (Creswell, 2014). Moreover, a survey also provided the ability to accurately make inferences about the population's characteristics limited to an accepted degree of error (Clow and James, 2014).

Although an experimental approach may have provided greater confidence in establishing *causality* between variables as observed in the study by Watson, Alexander and Salavati (2020), a survey-based approach still allowed the *inference of correlations* between variables in an economical manner (Bryman and Bell, 2011). Inferring correlations further enabled the validation of formulated hypotheses (Bryman and Bell, 2011). Also, unlike an experiment, this study took place in an uncontrolled environment without involving treatment/ intervention of the independent variables, and was therefore suitable for a survey (Creswell, 2014).

3.3. Instrument Design

3.3.1. Design and Layout

The survey was conducted using an online questionnaire. The questionnaire was created on Qualtrics using pre-existing scales to increase reliability and validity (Bryman and Bell, 2011). However, to suit the context of this study some scales were adapted, and a few original items were also developed. This was similar to the approach taken by other researchers who also used pre-tested scales (Creswell, 2014; Hsieh, Lee and Tseng, 2021; Lim *et al.*, 2021).

In line with the guidelines prescribed by Brace (2008), the questionnaire was structured in blocks as illustrated in Table 5. below. (Please see Table 6. for the code book used for this study and Appendix 3 - A 3.5. for the complete questionnaire).

According to Brace (2008), including more than 30 statements in the questionnaire may induce respondent fatigue. However, since this survey required the measurement of nine variables, behavioral data, and demographics, the questionnaire had a total of 38 statements. This was still less than some of the other questionnaires reviewed in literature which had around 46 – 68 statements (McLean *et al.*, 2019; Hsieh, Lee and Tseng, 2021; Lim *et al.*, 2021). While some other studies such as those of Antwi (2021) and Ali and Bhasin (2019) had about 30 questions, it is worth noting that these questionnaires did not seem to collect any behavioural data. Moreover, Antwi's (2021) sequence of collecting participant's background information before construct-related data may have induced respondent fatigue which wasn't accounted for.

Table 5: Block structure of the questionnaire designed.
Please see Appendix 3 – A 3.5 for the complete questionnaire.

Block	Design and Content
1. Cover Page	The research was introduced as a general consumer behaviour study on local multibrand fashion apps. **Any intimation about agile marketing capabilities in particular was avoided to minimize respondents predictability about any causal links between the constructs** (Clow and James, 2014). The jargon of 'Pureplay Multibrand Fashion App' was clarified with a simple definition and appropriate examples. A logo of UAL was also included to increase the authenticity of the research and make it worthy of the respondent's time. The cover page also outlined guidelines relating to voluntary participation, duration of survey, data protection and privacy disclosure, and consent.
2. Screening Questions	Two dichotomous (yes or no) screening questions regarding location and previous shopping experience with multibrand fashion apps were developed to funnel only those respondents who were based in the U.A.E and had purchased something at least once in the past two years from such apps. The two year time limit was proposed to account for any potential shopping breaks during the COVID 19 pandemic.
3. Behavioural Questions	Respondents were made to reflect on their app usage behaviour in order to position themselves for the upcoming attitudinal questions. This block included four nominal questions relating to most **commonly used app, purpose of use, frequency, and usage location**. **Allowing respondents to recall their behaviour before attitude would avoid eliciting spontaneous responses for the main constructs** (Brace, 2008). In addition, since one of the aims of this study was to develop managerial recommendations, asking behavioural questions provided rich insights to develop these recommendations.
4. Constructs (Attitudinal Questions)	Respondents were asked to indicate the level of disagreement/ agreement with various AMCs (i.e., independent variables), internal states (PAD), and repurchase intentions using five-point Likert scale items. Arousal and Pleasure were measured using five-point semantic differential scales. **Although seven-point Likert scales provide greater precision, five-point scales were used to make the questionnaire more user-friendly**. Each construct was measured with a **minimum of three items, in case of having to delete a scale on grounds of poor reliability and validity** (Hair *et al.*, 2010)**.**
5. Demographic Questions	**Gender, age, and occupation** related questions were asked at the end in order utilize greater attention span of the respondent for the behavioural and attitudinal questions at the beginning.
6. Lucky draw opt-in	Respondents interested in participating in the lucky draw could chose to input their contact details.
7. Note of Thanks	A short message conveying the researcher's gratitude and signaling that all responses had been recorded was displayed the end of the survey.

3.3.2. Mitigating Bias

Owing to the length of this questionnaire, various procedural and statistical remedies were adopted to minimize instrument and respondent bias. To control for acquiescence (tendency to agree) the Likert scale options were displayed from negative to positive. This would result in the 'least favorable response pattern', and hence a 'tougher test' for the hypotheses (Brace, 2008). To minimize primacy effect (tendency to recall first option), the options for nominal questions were randomized (Brace, 2008). Although McLean's (2019) study randomized the scales of constructs as well (to reduce Common Method Bias (CMB)), the options and order of Likert scale constructs were not randomized for this study. Randomization of Likert scale questions was avoided to ease the reader into the flow of the survey (Brace, 2008). Pattern responding and inattention was accounted for by including an Instruction Manipulation Check (IMC) (Oppenheimer, Meyvis and Davidenko, 2009; Hsieh, Lee and Tseng, 2021). The IMC was designed as a standard Likert scale question to camouflage with the other statements. It prompted respondents to tick the 'neutral' option in order to filter out those who did not pay attention. The survey also attempted to minimize attrition by motivating users to reach the end of the questionnaire to enter into the lucky draw (Clow and James, 2014). In addition, respondents were also given an idea of the duration it would take to complete the survey.

Apart from the procedural remedies, statistical testing using Harman's one factor test was also performed in order to eliminate the likelihood of CMB arising from self-selection bias as discussed in the data analysis in section 4.2 (Podsakoff *et al.*, 2003; Hsu and Chen, 2018).

3.3.3. Code Book

Table 6. presents the code book used for data analysis. It illustrates the various measurement items, data types, sources, and coding instructions for data analysis using SPSS V.27 and Smart PLS 3. It is important to note that the code book does not contain any demographic or behavioural questions (such as purpose of app usage, location, frequency). These have been recorded in the complete questionnaire presented in Appendix 3 – A3.5.

Table 6: Code Book containing all the variables used for hypotheses testing. Behavioral, Demographic, and Screening questions have been omitted from the code book. Refer to Appendix 3 - A 3.5. for the complete questionnaire containing all the questions.

	Constructs and Measurement Items	Source	Coding
AMCs – Antecedents. *Five-point Likert scale items*			
	Newness of Assortment		1 (Strongly Disagree) to 5 (Strongly Agree).
NoA_1	*This app sells various trendy fashion assortments.* Adapted	(Lim *et al.*, 2021)	
NoA_2	*This app offers fashion products with new designs.* Original		
NoA_3	*This app is up to date with new product launches.* Adapted		
NoA	*Total Score for Newness of Assortment*		Mean: A number out of 5 (=(3 x 5) / 3)
	Personalization		1 (Strongly Disagree) to 5 (Strongly Agree).
PER_1	*I feel this app can be personalized for my usage.* Adapted **(deleted post pilot)**	(Hsieh, Lee and Tseng, 2021)	
PER_2	*There are personalized contents in this app.* Adopted		
PER_3	*This app personalizes product recommendations to suit my taste.* Original		
PER_4	*This app displays personalized advertisements based on my usage.* Original		
PER	*Total score for Personalization.*		Mean: A number out of 5 (=(3 x 5) / 3)
	Transparent User Experience		1 (Strongly Disagree) to 5 (Strongly Agree).
TUX_1	*I know when my order has been shipped or is being compiled using this app.* Adopted	(Lim *et al.*, 2021)	
TUX_2	*The delivery information is readily available when using this app.* Adopted		
TUX_3	*I know when my order has been received using this app.* Adopted		
TUX_4	*This app has a transparent payment procedure.* Original		
TUX	Total Score for Transparent User Experience		Mean: A number out of 5 (=(4 x 5) / 4)
	Ubiquity		1 (Strongly Disagree) to 5 (Strongly Agree).
UBQ_1	*I can use this app anytime.* Adopted	(Hsieh, Lee and Tseng, 2021)	
UBQ_2	*I can use this app anywhere.* Adopted		
UBQ_3	*I expect the app would be available to use whenever I need it.* Adopted		
UBQ	Total Score for Ubiquity		Mean: A number out of 5 (=(3 x 5) / 3)
	After-Sales Services		1 (Strongly Disagree) to 5 (Strongly Agree).
AFS_1	*The after-sales services provided by this app are fast* Adapted	(Lim *et al.*, 2021)	
AFS_2	*The return/ exchange process using this app is fast.* Original		
AFS_3	*This app is quick to process any refund requests.* Original		
AFS	*Total Score for After-Sales Service.*		Mean: A number out of 5 (=(3 x 5) / 3)
Organism States – Mechanism. *Semantics Differential Scales and Five-point Likert scale items.*			
	Pleasure - *When I use this app, I feel:*		1 (Strongly Disagree) to 5 (Strongly Agree).
PLE_1	*Unhappy – Happy* Adopted	(Hsieh, Lee and Tseng, 2021)	
PLE_2	*Annoyed – Pleased* Adopted		
PLE_3	*Dissatisfied – Satisfied* Adopted		
PLE	*Total Score for Pleasure*		Mean: A number out of 5 (=(3 x 5) / 3)
	Arousal - *When I use this app, I feel:*		1 (Strongly Disagree) to 5 (Strongly Agree).
ARO_1	*Sleepy – Active* Original	(Hsieh, Lee and Tseng, 2021)	
ARO_2	*Calm – Excited* Adopted		
ARO_3	*Relaxed (laid-back) – Stimulated (energized)* Adapted		
ARO	*Total Score for Arousal*		Mean: A number out of 5 (=(3 x 5) / 3)
	Dominance		1 (Strongly Disagree) to 5 (Strongly Agree).
DOM_1	*I feel like I have a lot of control over my usage experiences on this app.* Adapted	(Hsieh, Lee and Tseng, 2021)	
DOM_2	*When I am on this app, I can choose freely what I want to see.* Adapted		
DOM_3	*While using the app, my actions decide the kind of experiences I get on this app.* Adapted		
DOM	*Total Score for Dominance*		Mean: A number out of 5 (=(3 x 5) / 3)
Repurchase Intentions – Outcome. *Five-point Likert scale items.*			

	Repurchase Intentions		1 (Strongly Disagree) to 5 (Strongly Agree).
RPI_1	*When I shop for fashion products online, I consider this app first.* Adapted	(Graciola *et al.*, 2018). Also adapted by Antwi (2021).	
RPI_2	*I do most of my online fashion shopping using this app.* Adapted		
RPI_3	*If I could shop online today, I would shop from this app again.* Adapted		
RPI_4	*I plan to do most of my future shopping from this app.* Adapted		
RPI	*Total score for Repurchase Intentions*		Mean: A number out of 5 (=(4 x 5) / 4)
Instruction Manipulation Check. *Five-point Likert scale item.*			
IMC	*Please select the 'Neutral' option for this statement. This is just to screen out random clicking.* *(Adapted. Camouflaged with the NoA statements).*	(Oppenheimer, Meyvis and Davidenko, 2009)	1 (Strongly Disagree) to 5 (Strongly Agree).

3.3.4. Piloting

A pilot study was conducted to ensure the instrument functions well, since self-completion questionnaires do not offer any opportunity to clarify questions from the researcher (Bryman and Bell, 2011). The survey was piloted with ten respondents consisting of four MA students, three working class participants previously residing in the UAE, and three current residents of the U.A.E. Since some of the pilot respondents were based in the EU or UK, two additional multibrand apps – ASOS and ZALANDO were included for respondents unfamiliar with local fashion apps from the U.A.E. In addition to this, the survey was also formally reviewed by two PhDs. Pilot respondents were asked to input their feedback at the end of questionnaire. Based on feedback received, the questionnaire was amended to reflect changes discussed in Appendix 3 – A 3.2.

3.4. Data Collection and Analysis

3.4.1. Data Collection and Target Population

The questionnaire was administered online on various social media platforms – LinkedIn, Instagram, WhatsApp, and Facebook, from August 11th to August 29th, 2021, using a call-for-research (Appendix 3 – A 3.2.). The target population for this study was *U.A.E-based males and females from the Gen Z (ages 18-24) and Younger Millennial (ages 25-29, 30-34) cohort who have purchased more than once from a local pureplay multi-brand fashion app in the past two years*, as these form the core fashion consumers highly likely to have engaged with mobile shopping (Euromonitor, 2020).

3.4.2. Sample Size

196 responses were recorded during the data collection period, out of which 56 were incomplete or did not meet the sampling criteria, and 12 failed the IMC. After discarding these, 128 valid responses were used for the final analysis. Although previous studies have used relatively larger sample sizes ranging from N=242 to N=893 (Hsu and Chen, 2018; De Canio, Fuentes-Blasco and Martinelli, 2021) to minimize sampling error, N=128 was well above the minimum sample size required for the PLS SEM analysis conducted in this research. In addition, according to Central Limit Theorem, since N>=30, the sample size was also suitable to achieve normal distribution required for supplementary analysis using SPSS (Clow and James, 2014).

According to Hair *et al.* (2014) there are two primary ways of determining the sample size for a PLS-SEM based study:

i. **The ten-times rule:** As a rule of thumb, the sample size should be equal to the larger of ten-times the greatest number of formative indicators used to measure a latent variable, or ten-times the maximum number of arrows pointing at a particular latent variable (Barclay, Higgins and Thompson, 1995). In the proposed conceptual model, the largest number of arrows directed at a latent variable are three (i.e., one arrow each from pleasure, arousal, and dominance pointing at repurchase intentions. See Figure 1.). Therefore, the minimum sample size required equals, $\mathbf{N_{min} = 10 \times 3 = 30}$.

ii. **Statistical power and minimum $\mathbf{R^2}$ method:** Assuming the common statistical power of 80%, Appendix 3 – A 3.3. can be used to determine the minimum sample size based on three factors – the greatest number of arrows pointing at an endogenous variable, minimum R^2 values in the endogenous construct, and the desired level of significance (Cohen, 1992). In the proposed model, the maximum number of arrows pointing at an endogenous variable is three (i.e., the three arrows from PAD pointing at repurchase intentions. See Figure 1.) and the desired level of significance is 5%. Therefore, as highlighted in the third row of Appendix 3 – A 3.3., the largest minimum sample size required for this study would be N_{min}= 124, assuming the least value of R^2.

The sample size for this study was **N=128, which is greater than $\mathbf{N_{min}}$= 30, and $\mathbf{N_{min}}$= 124**, and is hence, justified.

3.4.3. Sampling Technique

The respondents were sampled using non-probabilistic sampling, since it would be challenging to acquire a sampling frame using probabilistic sampling for the target population (Bryman and Bell, 2011). This approach was also adopted by other researchers, bearing in mind the challenges of a cross sectional study in terms of economy and time (Hsu and Chen, 2018; Antwi, 2021; De Canio, Fuentes-Blasco and Martinelli, 2021). While some studies used online consumer panels to achieve a more representative sample (Kim *et al.*, 2016; Hsieh, Lee and Tseng, 2021), others such as those of Ali and Bhasin (2019), and Parker and Wang (2016) were based on student and teacher sampling. Despite an adequate number of responses, the student sampling observed in these studies may have led to questionable reliability (Bryman and Bell, 2011; Ali and Bhasin, 2019). Therefore, to elicit responses from multiple demographics, this survey was launched on various online platforms which cater to different consumer groups, for example LinkedIn for working professionals, Instagram for creatives and students, etc. This approach was therefore a combination of convenience, snowball, and self-selection sampling used by several other researchers (Hsu and Chen, 2018; Antwi, 2021; De Canio, Fuentes-Blasco and Martinelli, 2021). Although the study commenced with quota sampling to increase reliability, the strategy had to be modified due to attrition and low response rates (see Appendix 3 – A 3.4. for the originally proposed quota).

3.4.4. Overview of Data Analysis

The data was analyzed used Smart PLS V 3.3.9 and SPSS V 27. Descriptive statistics and preliminary analysis were conducted using SPSS and MS Excel for graphs. Hypothesis testing was performed using Structural Equation Modeling (SEM) on Smart PLS. SEM was conducted in two stages- assessment of the measurement model followed by assessment of the structural model (Hair *et al.*, 2014; Hsu and Chen, 2018; De Canio, Fuentes-Blasco and Martinelli, 2021; Hsieh, Lee and Tseng, 2021).

Since non-probabilistic sampling is unsuitable for statistical tests, inference was based on the assumption that the sample is chosen randomly from an infinitely large population and follows normal distribution (Clow and James, 2014; Pallant, 2016). Though most of the data collected was ordinal, the use of any parametric tests on non-parametric data has been justified in extant literature (Jamieson, 2004).

Supplementary analysis was concluded on SPSS to study effects of demographics on consumers' repurchase intentions using T-test and ANOVA, observe any significant association between demographics and app usage behaviour using Chi Square tests, and account for non-response bias with independent sample T-tests .

3.5. Reliability and Validity

The reporting of SEM analysis requires the examination of a measurement model consisting of reliability and validity of constructs (Hair *et al.*, 2014). Therefore, the reliability and validity for this study has been discussed in more detail in the section on measurement modeling (Chapter 4).

Reliability was assessed using Cronbach's α and Composite Reliability (CR) (Hair *et al.*, 2014). Convergent validity was tested using the Average Variance Extracted (AVE). Discriminant validity was examined using the Fornell-Larcker criterion and HTMT ratios, and is discussed in Chapter 4 (Fornell and Larcker, 1981; Hair *et al.*, 2014).

Table 7. indicates the values of factor loadings of all reflective indicators (>0.7), CR (>0.7), Cronbach's α (>0.7), and convergent validity using AVE (>0.5) (Hair *et al.*, 2014; Hsu and Chen, 2018; McLean *et al.*, 2019; De Canio, Fuentes-Blasco and Martinelli, 2021; Hsieh, Lee and Tseng, 2021).

According to Hair *et al.* (2014), items slightly below the threshold loading maybe retained provided they contribute to the construct's validity and do not have loadings less than 0.4. Based on this, PER_1 was deleted despite having a factor loading > 0.7, since it compromised the AVE value for Personalization. PER_4 on the other hand, was retained despite having a factor loading < 0.7 since it contributed to an adequate composite reliability (>0.8) and AVE value (>0.5). Similarly, NoA_1 was also retained despite having a factor loading slightly less than 0.7 since it contributed to appropriate CR and AVE scores. All measures were retained with a minimum of three items as prescribed Hair *et al.* (2010).

Table 7: Reliability and Convergent Validity reported using Composite Reliability (CR), Cronbach's α, and Average Variance Extracted (AVE). See chapter 4 for detailed analysis of the measurement model.

Factor	**Loadings**
Newness of Assortment	**CR= 0.808**, Cronbach's α= 0.640, AVE= 0.588
NoA_1	0.637
NoA_2	0.839
NoA_3	0.808
Personalization	**CR= 0.813**, Cronbach's α= 0.665, AVE= 0.597 *(Excluding PER_1)*
PER_1 *(Deleted since AVE< 0.5)*	0.730
PER_2	0.872
PER_3	0.817
PER_4 *(Not deleted since AVE > 0.5 on retaining)*	0.604
Transparent User Experience	**CR= 0.902**, Cronbach's α= 0.857, AVE= 0.698
TUX_1	0.807
TUX_2	0.872
TUX_3	0.862
TUX_4	0.798
Ubiquity	**CR= 0.900**, Cronbach's α= 0.834, AVE= 0.749
UBQ_1	0.845
UBQ_2	0.866
UBQ_3	0.885
After Sales Service	**CR= 0.936**, Cronbach's α= 0.900, AVE= 0.831
AFS_1	0.917
AFS_2	0.929
AFS_3	0.888
Arousal	**CR= 0.848**, Cronbach's α= 0.733, AVE= 0.652
ARO_1	0.741
ARO_2	0.797
ARO_3	0.878
Dominance	**CR= 0.809**, Cronbach's α= 0.648, AVE= 0.586
DOM_1	0.743
DOM_2	0.761
DOM_3	0.792
Pleasure	**CR= 0.869**, Cronbach's α= 0.774, AVE= 0.688
PLE_1	0.781
PLE_2	0.852
PLE_3	0.854
Repurchase Intentions	**CR=0.917**, Cronbach's α= 0.879, AVE= 0.733
RPI_1	0.830
RPI_2	0.858
RPI_3	0.867
RPI_4	0.870

3.6. Limitations of Research Design

The cross sectional nature of this study may have potentially weakened causality and hence internal validity (Bryman and Bell, 2011). However, while some longitudinal studies such as that of McLean *et al.* (2019) had several merits, they did not account for non-response bias, especially in the second stage of the study, as other cross sectional studies did (Hsu and Chen, 2018). Therefore, this study, though cross sectional in nature, was made more robust by comparing demographic means of early and late respondents to eliminate any potential non-response bias (Clow and James, 2014). The sample size was also increased compared to the amount required for PLS-SEM analysis in order to minimize any sampling error and enhance the external validity of such a regional study (Clow and James, 2014). In addition, the questionnaire developed for this research was piloted to minimize non-sampling errors (such as wording of questions) possibly encountered during instrument design (Clow and James, 2014). Since the study encompasses differences in gender and age groups, the effect of these variables was also considered in supplementary tests reported in section 4.4.

3.7. Ethics

This research was designed in accordance with UAL's code of conduct, considering respect for persons, integrity, and respondents' privacy during data collection (UAL, 2017). The project was supervised with professional standards by the university-appointed faculty, and was devoid any forms of 'plagiarism, deception, fabrication, or falsification' in its findings (UAL, 2017). This research was not funded externally. Any expenses incurred were borne by the author. The minimum age required to participate in this study was 18 years. Respondents were asked for their consent before participating and were offered a lucky draw incentive in exchange for their time. The winning respondent was notified about their gift voucher without any public disclosure of their identity. All records were stored safely on password-protected systems. The study was also designed to present zero to minimal risks in terms of health and safety and was devoid of any conflicts of interest whether 'real, potential, personal, or professional' (UAL, 2017).

Chapter Four FINDINGS AND EVALUATION

4. Findings and Evaluation

4.1. Descriptive Statistics

As illustrated in Table 8., majority of the respondents were females (76.6%), while males accounted for about 20% of the responses. In terms of age, most of the participants were younger millennials aged 25 – 29 (41.1%), followed closely by Gen Zs aged 18 – 24 (39.1%), and core millennials aged 30 -34 (19.5%). Although these figures do not confirm to the UAE's actual gender distribution (70% males, 30% females), they do align with the country's age group distribution with more millennial respondents than Gen Zs (Global Data, 2020). Such demographic discrepancies were also observed in previous cross sectional studies (Antwi, 2021; De Canio, Fuentes-Blasco and Martinelli, 2021). The sample largely comprised of employed individuals (75.0%), but also included few students (19.5%) and miscellaneous occupations (5.5%), thereby making it more representative of the target population (Bryman and Bell, 2011).

Table 8: Sample's demographic and app behaviour distribution.

Variables	Categories	Frequency	Percentage
Gender	Male	25	19.5%
	Female	98	76.6%
	Preferred not to disclose	5	3.9%
Age	18-24	50	39.1%
	25-29	53	41.1%
	30-34	25	19.5%
Occupation	Student	25	19.5%
	Employed (Private sector/ Public Sector/ Self Employed)	96	75.0%
	Others (Family Manager/ Unemployed/ Prefer not to disclose)	7	5.5%
App Used	Namshi	76	59.4%
	Noon Fashion	32	25.0%
	6th Street	14	10.9%
	Sivvi	4	3.1%
	Styli	2	1.6%
Usage Location	At home	104	81.3%
	At work	12	9.4%
	On the commute	9	2.3%
	At place of study	3	7.0%
Usage Frequency	At least once a week	37	28.9%
	At least once a month	46	35.9%
	At least once in three months	24	18.8%
	At least once in six months	14	10.9%

At least once a year	3	2.3%
At least once in two years	4	3.1%

Namshi emerged as the most commonly used pureplay fashion app in the region (59.4%), followed by Noon (25.0%). Since Noon also retails other categories such as electronics and household items, compared to Namshi which specializes only in fashion and apparel, Noon may have outranked Namshi in other market analysis as their methodology was not limited to fashion categories (Euromonitor, 2021a). However, the results of this study indicate that Namshi has a potentially higher preference than Noon amongst consumers shopping solely for fashion. As expected from literature, 6th street was third in place (Euromonitor, 2021a). Most consumers used the app to purchase products (73.3%), browse for new trends (64.2%), and be up to date with discounts/ offers (46.7%), partly concurring with Mclean *et al*. (2019).

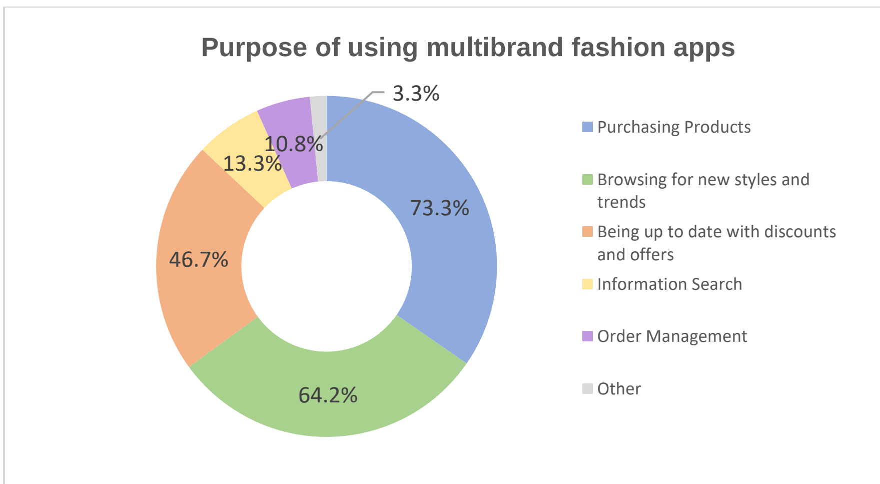

Figure 3:Pupose of using multibrand fashion apps.

Crosstabs were used to analyze the effects of gender and age on app usage location and frequency. Collectively about 81% of respondents usually accessed the app at home, largely diverging from McLean et al.'s (2019) study wherein most respondents used m-commerce apps while commuting, possibly due to geographic/ cultural differences in both samples. More males (32%) were potentially likely to use the app outside home than females (16.3%). While Millennials mostly used the app at home, over a quarter of Gen Zs were likely to be using the app outside of home. Close to two-thirds of the sample shopped using a pureplay fashion app at least once a month. Males seemed to be on fashion apps more frequently than females with 76% using an app at least once a month, compared to about 62.2% females. In terms of age, more Millennials (67%) were likely to use the app at least once a month than Gen Zs (62%). Following figures visually summarize the information captured by crosstabs. The detailed cross tabulations are reported in section 4.4.

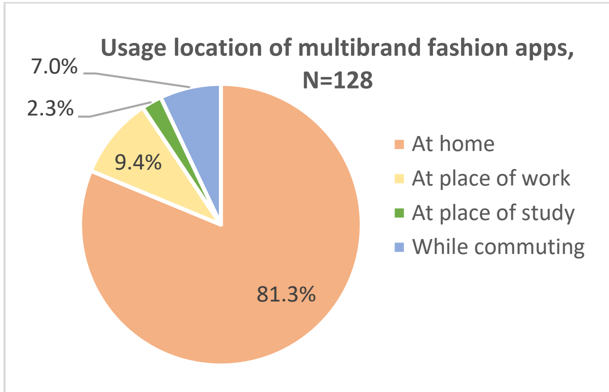

Figure 4: App usage location of multibrand fashion apps.

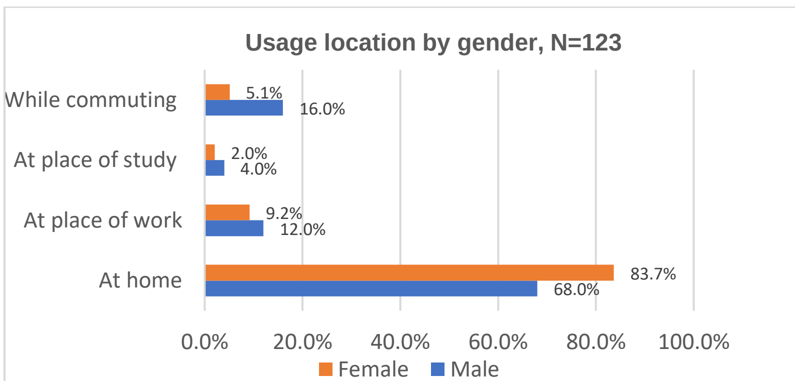

Figure 5: App usage location by gender.

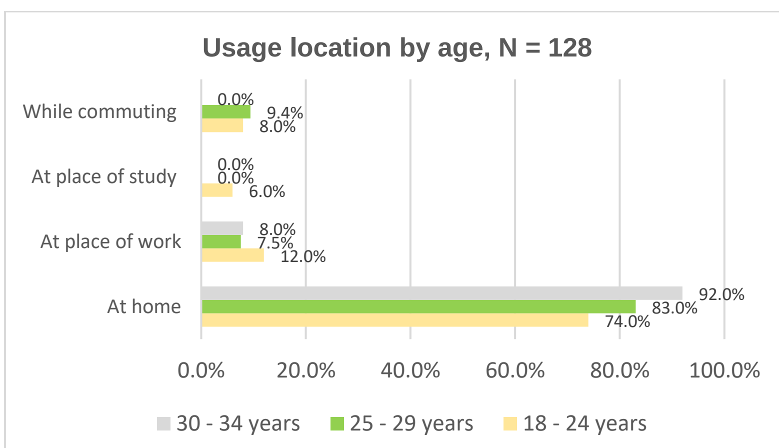

Figure 6: App usage location by age.

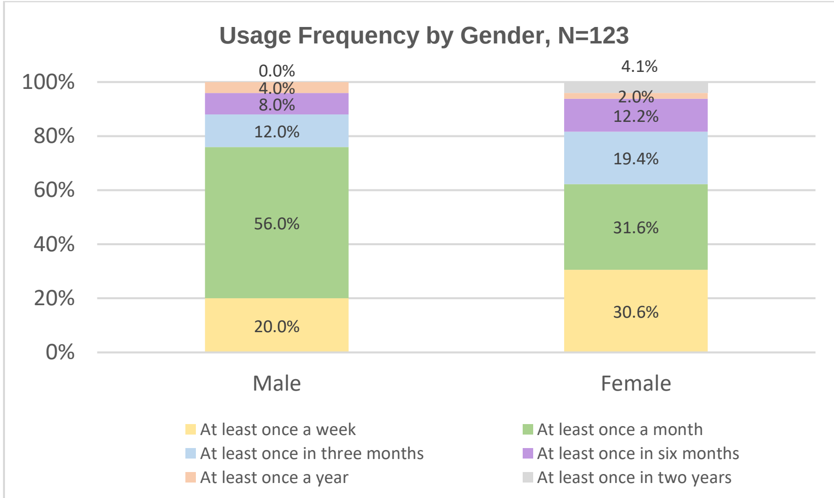

Figure 7: App usage frequency by gender.

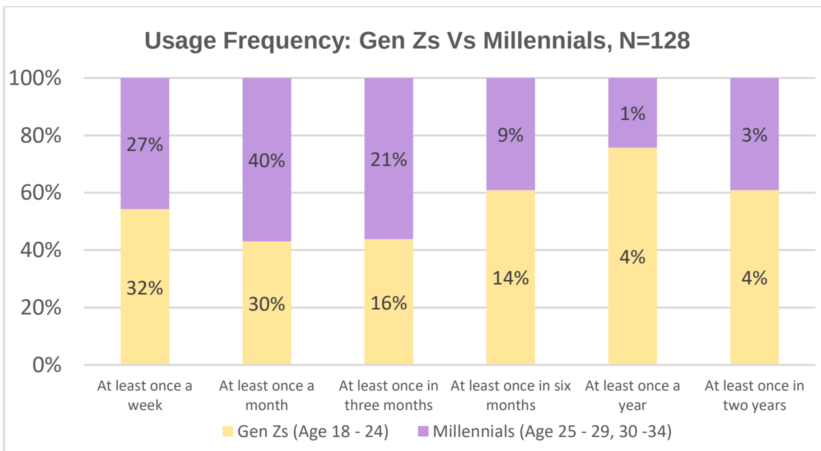

Figure 8: App usage frequency - Gen Zs Vs. Millennials.

As illustrated in Table 9., on an average most respondents were likely to have found their user experience to be transparent, convenient (ubiquitous), and pleasurable as indicated by the higher mean scores for TUX, UBQ and PLE compared to other constructs. Scores for PLE, ARO, and RPI had the highest standard deviations signaling that respondents may have largely differed on their attitudes regarding these constructs. The exact frequencies obtained for each construct have been reported in Appendix 3 – A 3.6.

Table 9: Descriptive statistics obtained for mean scores of all Variables used in hypotheses development.

Construct	Mean	Median	Mode	Std. Deviation	Minimum	Maximum
NoA	3.805	4.000	4.000	0.553	2.333	5.000
PER	3.440	3.333	4.000	0.665	1.667	5.000
TUX	4.225	4.000	4.000	0.588	2.500	5.000
UBQ	4.284	4.000	4.000	0.552	2.667	5.000
AFS	3.680	3.667	4.000	0.802	1.667	5.000
PLE	3.932	4.000	4.000	0.748	1.667	5.000
ARO	3.344	3.333	3.000	0.880	1.000	5.000
DOM	3.786	4.000	4.000	0.572	2.000	5.000
RPI	3.301	3.500	4.000	0.791	1.750	5.000

4.2. Preliminary Analysis

4.2.1. Normality

PLS SEM is based on the principles of non-parametric statistical analysis and therefore does not require the assumption of normality as other multivariate analysis do (Hair *et al.*, 2014). However, largely non-normal data may contribute towards incorrect assessment of the significance levels (Hair *et al.*, 2014). Thus, all the nine constructs were subjected to normality tests using SPSS V 27.

Normality results for the dependent variable, repurchase intentions (RPI) are illustrated below (normality of other variables is reported in Appendix 3 – A 3.7 and 3.8). As evident, RPI and all the other constructs were relatively normally distributed with reasonably straight normal Q-Q plots and most points collected around the zero line in detrended normal Q-Q plots (Pallant, 2016). Skewness and Kurtosis were within acceptable +1 and -1 range (Hair *et al.*, 2014; Pallant, 2016). Mean and 5% trimmed mean values were close, indicating an acceptable normal spread (Hair et al., 2014; Pallant, 2016). Although Kolmogorov-Smirnov and Shapiro-Wilk statistic were significant ($p < 0.05$), indicating violation of normality, such results are usually observed in larger samples (Clow and James, 2014; Pallant, 2016). Also, by Central Limit theorem, N>30, indicating data is normally distributed (Saunders *et al.*, 2019).

Table 10:Normality descriptives for RPI. Mean and 5% Trimmed Mean values are almost equal, indicating RPI data is normally distributed. Skewness and Kurtosis are within acceptable -1 and +1 limits for normality.

Construct	**Mean** Statistic Std. Error	**95% C.I for Mean** Lower Bound Upper Bound	**5% Trimmed Mean**	**Skewness** Statistic Std. Error	**Kurtosis** Statistic Std. Error
RPI	3.300 0.069	3.162 3.439	3.295	-0.074 0.214	-0.681 0.425

Table 11: Kolmogorov-Smirnov and Shapiro-Wilk's test for normality of RPI scores. Tested at $p < 0.05$ significance level. Although Kolmogorov-Smirnov and Shapiro-Wilk statistic are significant ($p < 0.05$), indicating violation of normality, such results are usually observed in larger samples.

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
Constructs	Statistic	df	Sig.	Statistic	df	Sig.
RPI	0.107	128	0.001	0.967	128	0.003
a. Lilliefors Significance Correction						

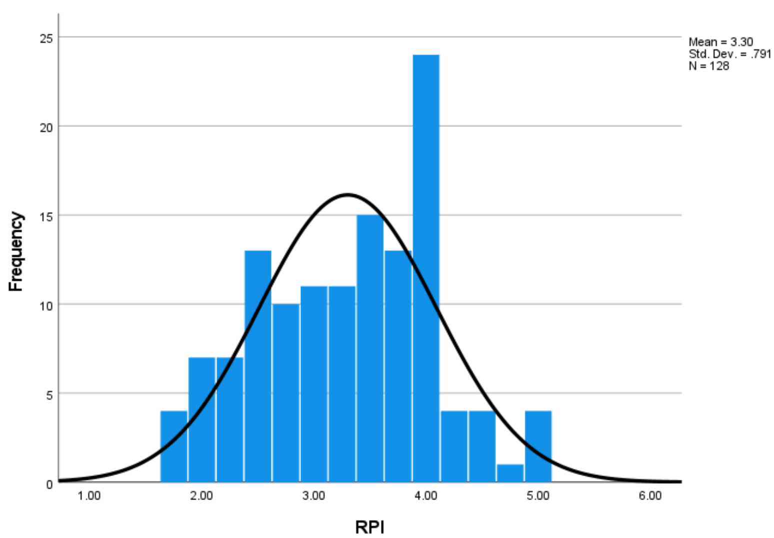

Figure 9: Histogram plot with normality curve for RPI scores.

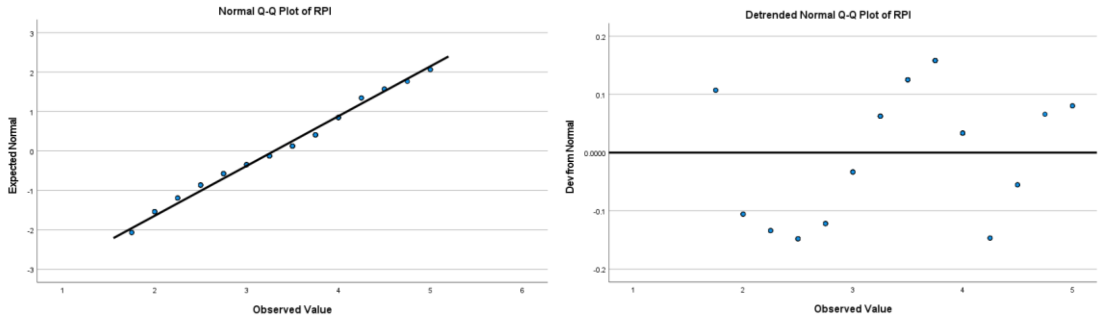

Figure 10: Normal Q-Q Plot and Detrended Normal Q-Q Plot of RPI.

4.2.2. Screening for Outliers

A total of 18 outliers were detected using box plots generated in the normality analysis. The outliers belonged to three constructs – NoA, PLE, and DOM. The mean and 5% trimmed mean values of the respective constructs were cautiously investigated and found to be approximately equal (see Appendix 3 – A 3.7.) , thereby permitting the retention of these data points in order to maintain an appropriate sample size for further analysis (Pallant, 2016).

Figure 11. displays the box plot for Repurchase Intentions as an example. The remaining box plots have been illustrated in Appendix 3 – A 3.8.

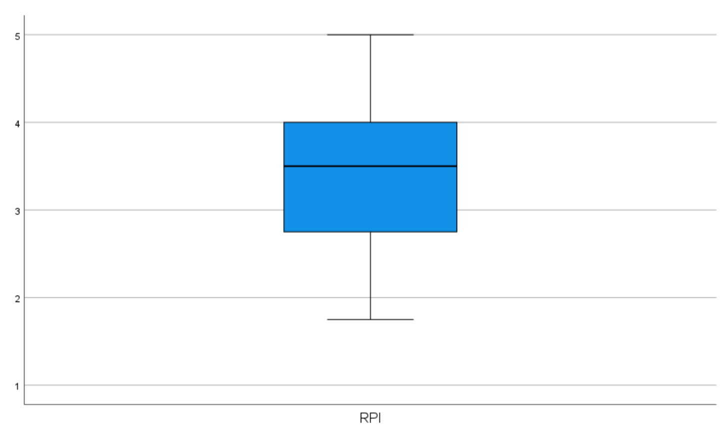

Figure 11: Box plot for RPI indicating absence of outliers.

4.2.3. *CMB (Harman's one-factor test)*

The measurement method used for this study may have induced CMB from various sources such as acquiescence, halo effect, respondent's social desirability, leniency effects, etc. (Podsakoff *et al.*, 2003). In the reviewed literature, researchers have assessed CMB using either of three statistical remedies – Harman's one-factor test (Hsu and Chen, 2018), Common method variance (Hsieh, Lee and Tseng, 2021), or Full collinearity based approach (Lim *et al.*, 2021). For the purpose of this study, CMB was tested using Harman's one-factor test by loading all items in an Exploratory Factor Analysis (EFA) with unrotated first factor. The total variance explained by the first factor was 26.6%, i.e. < 50%, confirming CMB was not a problem (see Appendix 3 – A 3.9.) (Podsakoff et al., 2003; Hsu and Chen, 2018).

4.2.4. *KMO and Bartlett's test of sphericity*

The KMO statistic was > 0.5 and Bartlett's test of sphericity was significant ($p < 0.001$), indicating that the variances in the variables were caused by underlying factors. Thus, the sample was adequate for factor analysis (Hsu and Chen, 2018; Ali and Bhasin, 2019). (Note: factor analysis was replaced with its PLS SEM equivalent - measurement model analysis, discussed in section 4.3).

Table 12: KMO and Bartlett's test of sphericity.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.771**
Bartlett's Test of Sphericity	Approx. Chi-Square	313.926
	df	36
	Sig.	**<.001**

4.3. Hypotheses Testing: PLS SEM

There are two ways to perform Structural Equation Modeling (SEM) for estimating relationships between variables – CB SEM (Covariance based approach), and PLS SEM (Partial Least Squares approach) (Hair *et al.*, 2010). Following the procedure adopted in extant literature, the paths hypothesized in this study were investigated using the PLS approach (Hsu and Chen, 2018; De Canio, Fuentes-Blasco and Martinelli, 2021; Hsieh, Lee and Tseng, 2021). The reason being, PLS provides greater statistical power when dealing with complex models and relatively low samples sizes compared to its covariance-based equivalent (Hair *et al.*, 2014). Although CB-SEM is suitable for theory confirmation, PLS offers explanatory/ verification modelling and flexibility with sample distributions (Hsu and Chen, 2018; Hsieh, Lee and Tseng, 2021). In addition, akin to multiple regression, PLS also provides stronger predictive capabilities based on OLS regressions to explain the model's 'partial regression relationships' (Hair *et al.*, 2014).

SEM was conducted in two stages using Smart PLS based on guidelines prescribed by (Hair *et al.*, 2014) :

i. **Outer Model aka Measurement Model assessment** – Involves empirical validation of the relationship between constructs and their respective indicators (scale items), by examining reliability and validity of the measures.

ii. **Inner Model aka Structural Model assessment** – Involves empirical validation of the relationships between various constructs (variables), i.e., the hypotheses and structural model.

4.3.1. Measurement Model (Outer Model)

Measurement model was evaluated using the foundations of principal component-based estimation in order to ascertain reliability and validity (De Canio, Fuentes-Blasco and Martinelli, 2021). The outer model comprised of three to four reflective indicators (arrows emerging out from the construct) for each of the nine variables. Internal consistency reliability was achieved since all CR values were greater than 0.7 (Hair *et al.*, 2014; Hsieh, Lee and Tseng, 2021). Cronbach's α was slightly below the 0.7 requirement for NoA, DOM, and PER. However, as prescribed by Hair *et. al* (2014), Cronbach's α is a conservative measure of reliability and should be used only secondary to CR which was already well above the threshold for all constructs. Convergent validity was established since all AVE values were > 0.5 (Hair *et al.*, 2014; Hsu and Chen, 2018).

As discussed in chapter 3 (Table 7.), almost all factor loadings were acceptable (> 0.7) (Hair *et al.*, 2014; Hsu and Chen, 2018). PER_1 was deleted despite having a factor loading above 0.7 since it plummeted the AVE to below 0.5, whereas NoA_1 and PER_4 were retained despite having loadings slightly less than 0.7, as their removal did not lead to a decrease in AVE below threshold (Hair *et al.*, 2014).

Discriminant validity was ascertained using the Fornell-Larcker Criterion and HTMT ratios. Square roots of all AVE values (i.e., the diagonal values in Table 14.) in the correlation matrix were greater than the construct's correlation with any other construct, and all HTMT ratios (see Table 15.) were lesser than 0.85 or 0.90, thereby confirming discriminant validity (Fornell and Larcker, 1981; Hsu and Chen, 2018).

Table 13: Composite Reliability (CR)< Cronbach's α and convergent validity (AVE). Cronbach's α > 0.6 retained since all CR > 0.7 and all AVE > 0.5 (Hair et al.*, 2014)*

Construct	CR	Cronbach's α	AVE
AFS	0.936	0.900	0.831
ARO	0.848	0.733	0.652
DOM	0.809	0.648	0.586
NoA	0.808	0.640	0.588
PER	0.813	0.665	0.597
PLE	0.869	0.774	0.688
RPI	0.917	0.879	0.733
TUX	0.902	0.857	0.698
UBQ	0.900	0.834	0.749

Table 14: Discriminant validity. Fornell-Larcker Criterion: Square root of AVE of a construct (i.e., the diagonal values in bold) should be greater than the construct's correlation with any other construct.

Construct	AFS	ARO	DOM	NoA	PER	PLE	RPI	TUX	UBQ
AFS	**0.911**								
ARO	0.090	**0.807**							
DOM	0.324	0.304	**0.765**						
NoA	0.148	0.403	0.308	**0.767**					
PER	-0.050	0.228	0.347	0.196	**0.773**				
PLE	0.247	0.509	0.410	0.315	0.276	**0.830**			
RPI	0.334	0.380	0.367	0.369	0.260	0.380	**0.856**		
TUX	0.553	0.220	0.446	0.286	0.138	0.383	0.193	**0.835**	
UBQ	0.454	0.170	0.348	0.321	0.047	0.326	0.196	0.615	**0.866**

Table 15: Discriminant validity evaluation using Heterotrait-Monotrait (HTMT) ratio. (should be less than 0.85 or 0.90) (Hair et al.*, 2014).*

Construct	AFS	ARO	DOM	NoA	PER	PLE	RPI	TUX	UBQ
AFS									
ARO	0.101								
DOM	0.424	0.431							
NoA	0.215	0.581	0.473						
PER	0.158	0.305	0.507	0.300					
PLE	0.282	0.682	0.580	0.459	0.372				
RPI	0.383	0.451	0.478	0.500	0.324	0.460			
TUX	0.617	0.285	0.583	0.398	0.190	0.460	0.221		
UBQ	0.527	0.225	0.457	0.430	0.079	0.396	0.223	0.729	

4.3.2. Structural Model (Inner Model) – Hypotheses Testing

The structural model was examined to evaluate the hypothesized relationships between constructs and the model's predictive capabilities, in order to conclude whether the theory could be confirmed empirically. Following steps were adopted in the assessment of the structural model:

i. Multicollinearity was examined to rule out its impact on the estimation of weights and significance levels. Variance Inflation Factor, i.e., VIF was below 5, and Tolerance was above 0.20 (see Table 19.). Thus, no threat of multicollinearity was observed, confirming data was suitable for SEM analysis (McLean *et al.*, 2019; Hsieh, Lee and Tseng, 2021; Lim *et al.*, 2021).

ii. The structural model was assessed using significance of paths (β, aka path coefficient), coefficient of determination (R^2), and predictive relevance (Q^2). 5000 resamples were generated at a 95% significance level (two-tailed) using the Bootstrapping function on Smart PLS to determine β and R^2 (Hair *et al.*, 2014). Blindfolding analysis was performed to investigate Q^2.

   R^2 values ranging from 0 to 1 are indicative of a model's increasing predictive power as they explain the variance in the endogenous variables (arrows going into the variable) brought about by the exogeneous/ independent variables. R^2 values for ARO, DOM, and RPI were above 0.1 indicating acceptable predictive capability, whereas PLE had a relatively low explanatory power (<0.1) , possibly due to the use of a single predictor (AFS) (Hair *et al.*, 2014; Hsieh, Lee and Tseng, 2021).

Q^2 values obtained for all endogenous constructs (ARO, DOM, PLE, and RPI) were above 0, confirming that the model has predictive relevance (Hair *et al.*, 2014; Hsu and Chen, 2018).

iii. Next, the hypotheses were tested to ascertain the significance of the relationships between constructs, based on threshold values of the T-statistic (t>1.96) and p value ($p < 0.05$) (Hair *et al.*, 2014; Lim *et al.*, 2021).

Newness of Assortment has significant positive influence on Arousal (H1: β = 0.373 , t = 4.378 , $p < 0.05$), whereas Personalization has an insignificant positive effect on Arousal (H2: β = 0.155 , t = 1.822 , $p = 0.069$).

Transparent User Experience is positively and significantly associated with feelings of Dominance (H3: β = 0.376 , t = 4.055 , $p < 0.05$), whereas Ubiquity has a small positive but insignificant effect on Dominance (H4: β = 0.112 , t = 1.167 , $p = 0.243$).

After-Sales Service has a significant positive relation with state of Pleasure (H5: β = 0.247 , t = 3.025 , $p < 0.05$).

Repurchase Intentions were significantly positively influenced by feelings of Arousal (H6a: β = 0.222 , t = 2.159 , $p < 0.05$) and Dominance (H6b: β = 0.234 , t = 2.421 , $p < 0.05$), but insignificantly by Pleasure (H6c: β = 0.171, t = 1.528 , $p = 0.127$).

iv. Effect size, f^2 was determined to examine a predictor's contribution to the R^2 value of corresponding endogenous construct. Drawing on Cohen's (1992) guidelines, NoA ($f^2 = 0.163$) and PER ($f^2 = 0.028$) had a medium and small effect on ARO respectively. TUX ($f^2 = 0.106$) and UBQ ($f^2 = 0.010$) had a medium and small effect on DOM respectively. ARO ($f^2 = 0.046$), DOM ($f^2 = 0.060$), and PLE ($f^2 = 0.025$) had small, small to medium, and small effects on RPI respectively (Lim *et al.*, 2021). Effect size of AFS on PLE was not estimated since the f^2 estimation requires minimum two predictors for a given construct. f^2 values were calculated using the below equation, where $R^2_{included}$ and $R^2_{excluded}$ refer to the R^2 values of an endogenous variable when a particular predictor is retained or dropped from the estimation the model (Cohen, 1992; Hair *et al.*, 2014).

Equation 1: Effect size calculation.

$$f^2 = \frac{R^2_{included} - R^2_{exluded}}{1 - R^2_{included}}$$

Model fit was assessed using SRMR (Standardized Root Mean Residuals) which was 0.080, i.e., below the threshold of 0.1, indicating that the data fits the model (Hsu and Chen, 2018).

Table 16. summarizes the results of the hypotheses discussed above.

It is important to note that although this study comprised of three intermediary variables (pleasure, arousal and dominance), it did not specifically hypothesize any mediating relationships in its objectives. This was similar to the approach adopted by Hsieh, Lee and Tseng (2021). The reason being, investigation of mediating effects would require the creation of additional paths from the five exogenous constructs (AMCs) towards repurchase intentions, thereby altering the predictive power (R^2) induced by the three intermediaries – pleasure, arousal, and dominance on repurchase intentions (Hair *et al.*, 2014). This would result in an alternate competing model which was beyond the scope of the present study.

Table 16: Summary of results obtained from hypotheses testing.

Path	Conclusion	β	STDEV	T Statistic	P Values
H1: NoA --(+)--> ARO, Newness of assortment is positively associated with feelings of arousal.	**Supported**	0.373	0.085	**4.378**	**0.000**
H2: PER --(+)--> ARO, Personalization is positively associated with feelings of arousal.	Not Supported	0.155	0.085	1.822	0.069
H3: TUX --(+)--> DOM Transparent user experience is positively associated with feelings of dominance.	**Supported**	0.376	0.093	**4.055**	**0.000**
H4: UBQ --(+)--> DOM, Ubiquity is positively associated with feelings of dominance.	Not Supported	0.112	0.096	1.167	0.243

H5: AFS --(+)--> PLE After-sales services are positively associated with feelings of pleasure.	**Supported**	0.247	0.082	**3.025**	**0.002**
H6a: ARO --(+)--> RPI Feelings of arousal have a positive influence on repurchase intentions.	**Supported**	0.222	0.103	**2.159**	**0.031**
H6b: DOM --(+)--> RPI Feelings of dominance have a positive influence on repurchase intentions.	**Supported**	0.234	0.097	**2.421**	**0.015**
H6c: PLE --(+)--> RPI Feelings of pleasure have a positive influence on repurchase intentions.	Not Supported	0.171	0.112	1.528	0.127

Table 17: R^2 and Q^2 values of endogenous constructs.

Endogenous Construct	R^2	Q^2
ARO	0.186	0.104
DOM	0.205	0.110
PLE	0.061	0.036
RPI	0.237	0.160

Table 18: Effect size, f^2, of various exogenous variables on corresponding endogenous constructs.

Predictor	Endogenous Construct	R^2 included	R^2 excluded	f^2
NoA	ARO	0.186	0.053	0.163
PER	ARO	0.186	0.163	0.028
TUX	DOM	0.205	0.121	0.106
UBQ	DOM	0.205	0.197	0.010
ARO	RPI	0.237	0.202	0.046
DOM	RPI	0.237	0.191	0.060
PLE	RPI	0.237	0.218	0.025

Table 19: VIF (< 5) and Tolerance values (> 0.20). Tolerance values are reported in brackets.

Construct	AFS	ARO	DOM	NoA	PER	PLE	RPI	TUX	UBQ
AFS						1.000 (1.000)			
ARO							1.371 (0.729)		
DOM							1.22 (0.819)		
NoA		1.04 (0.961)							
PER		1.04 (0.961)							
PLE							1.494 (0.669)		
RPI									
TUX			1.607 (0.622)						
UBQ			1.607 (0.622)						

4.4. Supplementary SPSS analysis

In order to provide deeper managerial insights, the means of demographic and behavioural data were compared on SPSS. These included investigation of:

- Any potential association between demographics and repurchase intentions (T-test and one way ANOVA)
- Potential association between demographics and usage location, and between demographics and usage frequency (Cross tabulations and Chi Square test for Independence)
- Non-response bias (Independent sample T-test).

i. Effects of demographics (age, gender and occupation) on consumers' repurchase intentions (RPI).

- *Independent sample T-test was conducted to compare mean RPI scores of male and female respondents.*

  Assumptions: Dependent variable RPI was continuous (since mean scores are continuous) and normally distributed, random sampling, observations were independent/ collected in non-group settings. However, Levene's statistic was significant (p < 0.05), therefore equal variances were not assumed (Pallant, 2016).

There was an **insignificant difference between the RPI scores for males** (*M*= 3.360, *SD* = 0.595) **and females** (*M*= 3.290, SD = 0.851); *t* (52.066) = 0.417, *p* = 0.640, confirming males are not significantly more likely to engage in repeat purchases than females.

Table 20: Independent sample T-test comparing RPI means of male and female respondents. p < 0.05 significance level.

	Male			Female			**T-test for equality of Means**				
	n	***M***	***SD***	***n***	***M***	***SD***	***Mean Difference***	***95% CI***	***df***	***t***	***p (Sig. 2-tailed)***
RPI *(Equal variances not assumed, p<0.05 Levene's test)*	25	3.360	0.595	98	3.291	0.852	0.069	-0.225, 0.363	52.066	0.471	**0.640**

- *One way between-groups ANOVA was performed to observe the effects of different age groups on consumers' repurchase intentions.*

Assumptions: Dependent variable RPI was continuous (since mean scores are continuous) and normally distributed, random sampling, observations were independent/ collected in non-group settings. Levene's test was insignificant (*p* = 0.079) confirming homogeneity of variances (Jamieson, 2004; Pallant, 2016).

Overall, results of ANOVA indicate a statistically significant difference at the 95% significance level among the repurchase intentions of different age groups, *F*(2, 125) = 3.739, *p* < 0.05. Post-hoc comparisons using Tukey HSD test reveal that **older millennials aged 30-34** (*M*=3.6700, *SD*= 0.60260) **were significantly more likely to engage in repeat purchases than Gen Zs aged 18 - 24** (*M*=3.1600, *SD*= 0.82648). However, no significant differences were detected between repurchase intentions of Gen Zs and younger Millennials (age 25 -29), and between older and younger millennials.

*Table 21: One way between-groups ANOVA to test the effects of different age groups on RPI. (*p < 0.05 level of significance, 2- tailed).*

				Test of Homogeneity of Variances		ANOVA	
Age Groups	***n***	***M***	***SD***	***Levene's Statistic***	***Sig.***	***F (2, 125)***	***Sig. (2-tailed)***
18-24	50	3.1600	0.82648	2.588	0.079	3.739	**0.026***
25-29	53	3.2594	0.79506				
30-34	25	3.6700	0.60260				
Total	128	3.3008	0.79142				
Group Differences							
Age Groups	***Mean Difference***	***Sig. (2-tailed)***	***95% CI***				
(18-24) - (25-29)	-0.09943	0.792	-0.4618	0.2629			
(25-29) - (30-34)	-0.41057	0.078	-0.8565	0.0354			
(18-24) - (30-34)	-.51000*	**0.022***	-0.9602	-0.0598			

- One way between-groups ANOVA for various occupations and repurchase intentions indicates **an insignificant difference among the repurchase intentions of people working in different sectors**, F (6, 121) = 1.873 , p = 0.091.

Table 22: One way between-groups ANOVA to test the effects of different occupations on RPI. (p < 0.05 level of significance, 2-tailed). Note Levene;s Statistic was significant (p = 0.947), confirming homogeneity of

				Test of Homogeneity of Variances		ANOVA	
Age Groups	***n***	***M***	***SD***	***Levene's Statistic***	***Sig.***	***F (6, 121)***	***Sig. (2-tailed)***
Student	25	2.9600	0.75925	0.947	0.453	1.873	**0.091**
Public sector-employed	6	3.7083	0.85756				
Private sector-employed	78	3.3814	0.80856				
Self-employed	12	3.0417	0.59193				
House manager/ Family manager	1	4.0000					
Unemployed	4	3.8125	0.51539				
Prefer not to disclose	2	3.3750	0.53033				
Total	128	3.3008	0.79142				

ii. **Association between Demographics (age, gender) and App Usage Behaviour (location, frequency) .**

- *Chi Square test for Independence was performed using cross tabs to confirm if there was any association between categorial variables age and gender, and app usage frequency and location.*

  Assumptions: Random sampling and independent observations. Yate's continuity correction was used instead of Pearson Chi Square statistic, and Phi instead of Cramer's V, since all analysis were for a 2 X 2 matrix (Pallant, 2016). *p* value was reported using Fisher's Exact test for grids which violated the minimum cell frequency assumption (i.e., at most 20% of cells can have expected count less than 5) (Pallant, 2016).

- App Usage Location (at home vs. outside home) and Gender (male vs. female): Chi Square Test for Independence (with Yate's Continuity Correction and Fisher's Exact Test) indicated an **insignificant association between gender and app usage location**, X^2 (1, 123) = 2.198, *p* = 0.073, *phi* = 0.093 (See Table 24.).

Table 23: Gender X App Usage Location Crosstabulation.

Gender * Location Crosstabulation					
			App usage location		Total
			At Home	Outside Home	
Gender	Male	Count	17	8	25
		% within gender	68.0%	32.0%	100.0%
	Female	Count	82	16	98
		% within gender	83.7%	16.3%	100.0%
Total		Count	99	24	123
		% within gender	80.5%	19.5%	100.0%

Table 24: Chi Square test of Independence for Gender X App Usage Location. (p < 0.05 significance level, 2-tailed).

Gender * Location Chi-Square Tests					
	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	3.116[a]	1	0.078	0.093	0.073
Continuity Correction[b]	**2.198**	1	0.138		
Fisher's Exact Test				0.093	**0.073**
N of Valid Cases	123				
a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 4.88.					
b. Computed only for a 2x2 table					

- App Usage Location and Age (Gen Zs vs. Millennials): Chi Square Test for Independence (with Yate's Continuity Correction) indicated an **insignificant association between age and app usage location**, X^2 (1, 128) = 2.104, *p* = 0.147, *phi* = 0.092 (Table 26.).

Table 25: Age X App Usage Location Crosstabulation.

Age * Location Crosstabulation					
			App usage location		Total
			At Home	Outside Home	
Age	Gen Zs	Count	37	13	50
		% within age	74.0%	26.0%	100.0%
	Millennials	Count	67	11	78
		% within age	85.9%	14.1%	100.0%
Total		Count	104	24	128
		% within age	81.3%	18.8%	100.0%

Table 26: Chi Square test of Independence for Age X App Usage Location. (p <0.05 level of significance, 2-tailed).

Age * Location Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	2.831[a]	1	0.092
Continuity Correction[b]	**2.104**	1	**0.147**
N of Valid Cases	128		
a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.38.			
b. Computed only for a 2x2 table			

- App Usage Frequency (high frequency vs. low frequency) and Gender (male vs. female): Chi Square Test for Independence (with Yate's Continuity Correction) indicated an **insignificant association between gender and app usage frequency**, X^2 (1, 123) = 1.108, p = 0.293, *phi* = 0.116 (Table 28.).

Table 27: Gender X App Usage Frequency Crosstabulation.

Gender * Frequency Crosstabulation					
			App Usage Frequency		
			High Frequency Users	Low Frequency Users	Total
Gender	Male	Count	19	6	25
		% within Gender	76.0%	24.0%	100.0%
	Female	Count	61	37	98
		% within Gender	62.2%	37.8%	100.0%
Total		Count	80	43	123
		% within Gender	65.0%	35.0%	100.0%

Table 28: Chi Square Test of Independence for Gender X App Usage Frequency. (p < 0.05 level of significance, 2-tailed).

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	1.657[a]	1	0.198
Continuity Correction[b]	**1.108**	1	**0.293**
N of Valid Cases	123		
a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 8.74.			
b. Computed only for a 2x2 table			

- App Usage Frequency and Age (Gen Zs vs. Millennials): Chi Square Test for Independence (with Yate's Continuity Correction) indicated an **insignificant association between age and app usage frequency**, X^2 (1, 128) = 0.122, p = 0.726, *phi* = 0.705 (Table 30.).

Table 29: Age (Cohort) X App Usage Frequency Crosstabulation.

Age (Cohort) * Frequency Crosstabulation					
			App Usage Frequency		Total
			High Frequency Users	Low Frequency Users	
Age (Cohort)	Gen Zs	Count	31	19	50
		% within age	62.0%	38.0%	100.0%
	Millennials	Count	52	26	78
		% within age	66.7%	33.3%	100.0%
Total		Count	83	45	128
		% within age	64.8%	35.2%	100.0%

Table 30: Chi Square Test of Independence for Age (Cohort) X App Usage Frequency. ($p < 0.05$ significance level, 2-tailed).

Age (Cohort) * Frequency Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	.291[a]	1	0.590
Continuity Correction[b]	**0.122**	1	**0.726**
N of Valid Cases	128		
a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 17.58.			
b. Computed only for a 2x2 table			

iii. Nonresponse bias

As observed in the study by Hsu and Chen (2018), demographic means of early and late respondents were compared using independent samples t- test, to minimize the likelihood of non-response bias. Results reveal that there were **no significant differences in the means of age (t(125.073) = -1.555, p = 0.122), gender (t(124) = 0.444, p = 0.658), and occupation (t(126) = 0.729, p = 0.468) of early and late respondents, thereby minimizing the chances of nonresponse**. Although gender and occupation were non-ratio variables (unlike age), the use of such parametric tests on non-continuous scores has been justified in extant literature (Jamieson, 2004; Hsu and Chen, 2018).

Table 31: Independent sample T-test confirming no differences observed in the mean scores of age, gender, and occupation between early and late respondents. (p < 0.05 significance level, 2-tailed).

	Early Respondents			Late Respondents			**T-test for equality of Means**				
	n	***M***	***SD***	***n***	***M***	***SD***	***Mean Difference***	***95% CI***	***df***	***t***	***p (Sig. 2-tailed)***
Age *(Equal variances not assumed, p=0.047 Levene's test)*	64	1.7031	0.77007	64	1.9063	0.70640	-0.20313	-0.461, 0.055	125.073	-1.555	**0.122**
Gender *(Equal variances assumed, p > 0.05 Levene's test)*	64	1.8594	0.43158	62	1.8226	0.49668	0.03679	-0.127, 0.200	124	0.444	**0.658**
Occupation *(Equal Variances Assumed, p > 0.05)*	64	2.9063	1.34186	64	2.7500	1.06904	0.15625	-0.268, 0.580	126	0.729	**0.468**

4.5. Structural Model

Figure 12. illustrates the final structural model obtained after running the proposed conceptual model on Smart PLS. Blue circles denote the variables used in hypotheses testing. Yellow rectangles represent the items that make up each construct. Paths between the construct denote the vales of path coefficients and T- statics (in bracket). The values reported inside each endogenous variable denote R^2, indicating the amount of variance resulting from the corresponding exogenous constructs. For example, 23.7 % of the variance observed in repurchase intentions results from arousal, dominance, and pleasure. Figure 13. depicts a partially refitted version of the model (excluding effects of age), demonstrating all the significant and insignificant paths at $p < 0.05$ level, two-tailed.

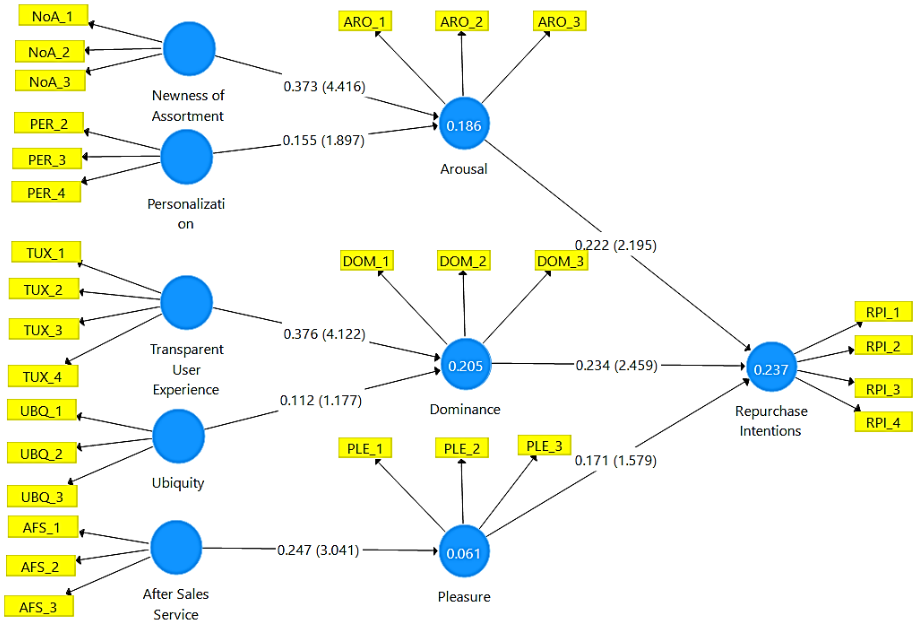

Figure 12: Structural Equation Model Output obtained from Smart PLS 3 for N = 128. All arrows report the path coefficients and t-statistic (in bracket). Path is significant if t-statistic > 1.96. R^2 values are reported inside the blue circles for all endogenous constructs. ($p < 0.05$, 2-tailed).

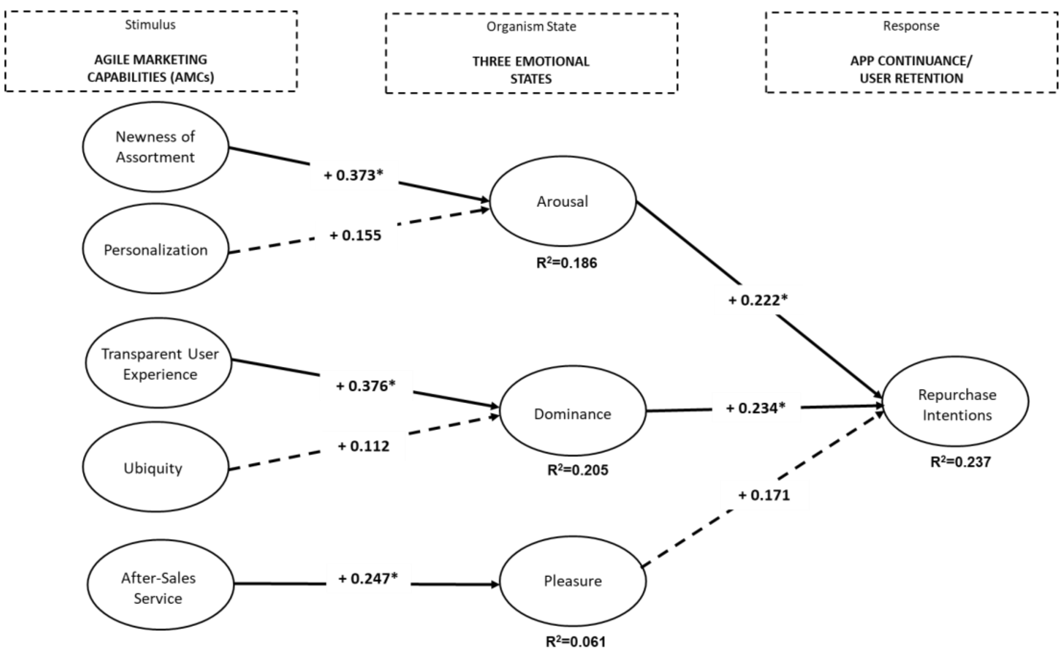

Figure 13: Structural Model depicting the significant paths.
Dashed arrows indicate that the path is insignificant. ($p < 0.05$, 2-tailed), N= 128.*

Chapter Five DISCUSSION AND CONCLUSION

5. Discussions and Conclusion

5.1. Theoretical implications

Drawing on the limitations articulated in extant literature, this research sought to examine agile marketing capabilities empirically from a consumer perspective, by building on previous exploratory organizational studies on the topic. The study employed the principles of Mehrabian and Russell's (1974) Environmental Psychology to investigate the combined effects of AMCs and consumer's emotional states on fashion repurchase intentions. Simultaneously, the study also aimed to address contextual gaps in existing app marketing academia by basing its findings particularly on pureplay multibrand fashion apps in the UAE.

To begin with, the study adds further knowledge to the *qualitative* nascent literature on agile marketing in the domain of fashion apps by operationalizing AMCs into five dimensions – newness of assortment, personalization, transparent user experience, ubiquity, and after-sales service, based on similar constructs investigated in earlier *quantitative* studies. Next it demonstrates that AMCs, when considered as a marketing stimuli in the digital environment of fashion apps, can influence users' affective states which in turn may impact purchase behaviour, thereby validating the application of the S-O-R theory in the context of pureplay multibrand fashion apps (Mehrabian and Russell, 1974). Overall, the study highlights emotions of dominance and arousal as key precursors of repeat purchases in comparison to pleasure. It also demonstrates how arousal and dominance in turn are strongly influenced by trendier fashion collections and a platform's transparency, respectively.

Findings reveal that newness of assortment significantly influences feelings of arousal. This is in confirmation with Lim *et al.* (2021) whose research illustrates positive effects of assortment and marketing mix on consumer engagement. Considering the common aspect of 'excitement' between engagement and arousal, this finding suggests that consumers are excited by trendy designs and new launches, as expected (Moi and Cabiddu, 2020; Kotler, Kartajaya and Setiawan, 2021). This also aligns with the behavioural data collected in this study, which shows browsing for new styles and trends is main purpose of using fashion apps, besides shopping itself (see Figure 3, Chapter 4). However, while newness of assortment emerges as a relatively strong precursor of arousal, personalization does little to create a similar sense of excitement in pureplay fashion apps. Though other authors highlight the importance of human touch from personalized and anthropomorphic features as a key driver of engagement in mobile apps (Kim *et al.*, 2016; Lim *et al.*, 2021), this study suggests that the effects of personalization on users' excitement levels are rather insignificant. This could probably be because users in the current context either did not experience enough personalized content that could stimulate them (as indicated by the relatively lower mean scores and higher standard deviations for personalization, Table 9.), or simply experienced a drop in engagement levels as a result of overexposure to personalized content in the form of remarketing ads, YouTube ads, push notifications, and a constant influx of promotional emails (Bretous, 2021).

As expected, further results demonstrate that transparent user experience is a largely significant precursor of dominance. This assents with several existing findings that evidence the positive effects of features such as informativeness, delivery quality, perceived informativeness and channel transparency on app continuance (Kim *et al.*, 2016; Ali and Bhasin, 2019; Hsieh, Lee and Tseng, 2021; Lim *et al.*, 2021). This also follows Chiu *et al.'s* (2014) correlation between perceived risk and utilitarian value in the sense that transparency constitutes a form of utilitarian agility which reduces consumer's perceived risk, thereby enhancing control over the shopping experience.

In comparison to transparency however, the mere ubiquity of mobile apps is not enough to elicit feelings of dominance. This diverges from existing literature that shows a positive association between ubiquity/ perceived ubiquity and dominance (Kim *et al.*, 2016; Hsieh, Lee and Tseng, 2021). Insignificance of ubiquity is also evident considering that most consumers preferred to access the app at home (see Table 8.). This suggests that despite the country's high internet penetration, mobile data in the UAE could probably be expensive for customers of high street fashion apps (The World Bank, 2019). Users subscribing to data packages could probably be using it for faster, routine tasks like e-mail and WhatsApp messaging, unlike shopping which is relatively more time consuming. Others having access to public Wi-Fi networks would probably be insecure about leaking payment credentials from shopping apps on insecure networks. These findings highlight the need to complement the tangible ubiquitous aspect of mobile apps with agile transparent process. These may include real-time updates, safe and transparent payments, and dynamic fixes, to build a mobile environment which, despite lack of physical touchpoints, can still provide consumers with a strong sense of control and continuity over their shopping experience (Hsieh, Lee and Tseng, 2021; Kotler, Kartajaya and Setiawan, 2021).

In terms of post-delivery agility, after-sales service significantly improved consumer's happiness levels within multibrand fashion apps, concurring with expectations from literature (Ali and Bhasin, 2019; Lim *et al.*, 2021) . However, the relatively lower coefficient of determination obtained for this association signals that there are potentially several other factors besides an efficient and flexible post-delivery system which contribute to users' overall happiness, such as gamification and incentivization (Hsu and Chen, 2018; Tseng, Hsieh and Lee, 2021) . As illustrated in literature, some of these include even non-agile features such as entertainment, aesthetics, and shopper's hedonic orientation (Chiu *et al.*, 2014; Hsu and Chen, 2018; Hsieh, Lee and Tseng, 2021), indicating that agility is perhaps not the single most efficient antecedent of pleasure.

Out of the three emotional states, this study exhibits that dominance has the strongest impact on repurchase intentions, thereby corroborating with findings from Hsieh, Lee and Tseng (2021) who assert positive links between dominance and app continuances, and Ali and Bhasin (2019) who ascertain positive effects of consumer trust (sense of reliability/ control) on repeat purchases. This also aligns with research from Chiu et al., (2014) which states perceived risk *negatively* moderates the path between utilitarian benefits and repeat purchases. Thus, when perceived risk is low (i.e., dominance/ control is high), utilitarian benefits such as the platform's transparency are likely to influence app usage continuance. Almost at par with dominance, arousal too significantly influences fashion repurchases as expected based on several findings illuminating the effects of arousal and consumer engagement on purchase behaviour (De Canio, Fuentes-Blasco and Martinelli, 2021; Hsieh, Lee and Tseng, 2021; Lim *et al.*, 2021; Tseng, Hsieh and Lee, 2021). However, while other studies examine emotional states within their respective contexts such as gamification, anthropomorphism, single brand apps, or general m-commerce, this study investigates the effects of emotions derived specifically from agile marketing stimuli in a pureplay multibrand context.

Surprisingly, this research reveals that while pleasure does influence repurchase intentions slightly positively, these effects are *not* significant. This implies that just because consumers may be happy with a particular fashion app platform, pleasure alone is not sufficient enough to engage them in repeat purchases. This contradicts findings from other academics who have established significant associations between pleasure / enjoyment and purchase behaviour (McLean *et al.*, 2019; De Canio, Fuentes-Blasco and Martinelli, 2021; Hsieh, Lee and Tseng, 2021). However, the insignificant association between pleasure and repeat purchases observed in this study does agree with findings of Antwi (2021) which show that customer satisfaction (a form of pleasure) does not influence repurchase intentions. This could also indicate a previously unexplored geographical justification, as both the present study and that of Antwi's (2021) took place in the MENA region, whereas contradictory findings from other authors cited were derived from studies conducted in the UK and Asia Pacific regions. Perhaps consumers in the MENA region are exposed to satisfactory levels of after-sales service from most apps (making customer satisfaction a non-differentiator), or simply derive greater pleasure from shopping on other formats. The non-significance of pleasure and relatively lower significance of arousal (as a hedonic emotions) compared to dominance (which is more utilitarian) , is also in line with other findings which demonstrate that hedonic values are weaker predictors of repeat purchases than utilitarian values (Chiu *et al.*, 2014).

5.2. Managerial implications

Apart from theoretical contributions, the findings from this study offer several practical implications for industry professionals. These findings would be of particular interest to fashion app marketers and app developers who are constantly seeking to optimize user retention for their mobile platforms.

One of the key implications of this study is that AMCs have an indirect impact on consumers' repurchase intentions. This effect is facilitated by users' emotional states. Therefore, if marketers want to drive user retention, they should work backward by first mapping the emotions that influence repeat purchases, and then identifying the AMCs which trigger these emotions (see Figure 14. below).

Firstly, marketers should consider eliciting feelings of dominance in the users of their apps. This would help impart a sense of control and minimize consumers' perceived risk. To do so, marketers can focus on building a transparent user experience in collaboration with the product development team. The app interface could include designated sections for order tracking coupled with timely push notifications and email alerts (Hsieh, Lee and Tseng, 2021; Lim *et al.*, 2021). Visibility of key contact information such as customer service number, email, and delivery valet's contact could be enhanced with prominent placements. Most pureplay fashion apps in the UAE still lack virtual helpdesks, when compared to app interfaces in western countries (Lim *et al.*, 2021). Thus, marketers can leverage tools like chatbots to further enhance transparency. Out of all the apps studied, only STYLI seemed to have a similar feature in the form of WhatsApp for Business, using which consumers can directly chat with a representative. Other apps may want to consider leveraging such tools before being left behind by emerging competitors. In addition, content marketers could also produce detailed copy and leverage other formats of product display such as video catwalks used by ASOS or AR try-ons used by Farfetch (Fish, 2019; McDowell, 2021). This would help shoppers who are prone to second-guessing in minimizing their uncertainty. Social teams can also build transparency outside the app by hosting live streaming and Q&A sessions to help customers clarify any grey areas.

Following dominance, feelings of arousal also influence repurchases significantly. Accordingly, user experience designers should consider providing functionality that stimulates or excites users to return to the app. This study identifies newness of a platform's fashion assortment has one of the key triggers of user excitement. Marketers are therefore advised to be agile in terms of scouting the latest trends and forecasting accurate demand, preferably using Artificial Intelligence (Kotler, Kartajaya and Setiawan, 2021). New trends could also be scouted from users themselves by studying their in-app search history or embedding camera search functionality like ASOS's Style Match feature to display new assortments personalized to the user's taste (Canales, 2018). Managers may also consider signing exclusive contracts with the brands being retailed on their mobile stores. However, since multibrand apps usually have a significant number of overlapping brands, implementing exclusivity might be challenging. For example, among the top ten brands stocked on the apps discussed in this study, key brands like Mango, Nike, adidas, Tommy Hilfiger, and Calvin Klein are available at almost all the apps (Edited Market Analytics, 2021). Perhaps multibrand apps can consider collaborating with local artists or bigger brands to launch new and exclusive collections, or hype regular collections with VIP programs, remarketing ads, and pop-up experiences.

This study further highlights that feelings of pleasure do not necessarily lead to repeat purchases indicating that most m-commerce providers in the region must be at par in terms of customer satisfaction (Antwi, 2021). However, for emerging apps or apps struggling with customer happiness, this study reveals the significance of after-sales service as a key driver of pleasure. Thus, managers should consider deploying an agile warehousing and logistics network to ensure smooth returns and exchanges (Moi and Cabiddu, 2020). They could also offer gifts with purchase for high value customers or differentiate in the after-sales space with repair services to enhance customer happiness.

Importantly, this study also shows that Gen Zs in U.A.E are significantly less likely to repurchase from local apps compared to older Millennials (section 4.4.). This should alert regional marketers to boost retention programs for younger consumers who are soon to become core category shoppers. Gen Zs could be dropping out either to shop from budget stores like SHEIN, or vintage stores on Instagram, or escalating towards purpose-driven brands (Edelman, 2018; Ahmed *et al.*, 2019). M-commerce managers may therefore consider resonating with Gen Z-centric values like purpose and community in order to retain the cohort. In addition, though statistically insignificant, Gen Zs were also more likely use the app outside their homes. Therefore, marketers could also build agility with geomarketing (Hsieh, Lee and Tseng, 2021) by sending push notifications during common commute times, or build offline functionality like Netflix to enhance the app's ubiquity for such users. Lastly, the study dismisses any significant effects of gender and age on consumer's app usage frequency and location signaling the need to build timely and location-specific content for all users irrespective of their demographics.

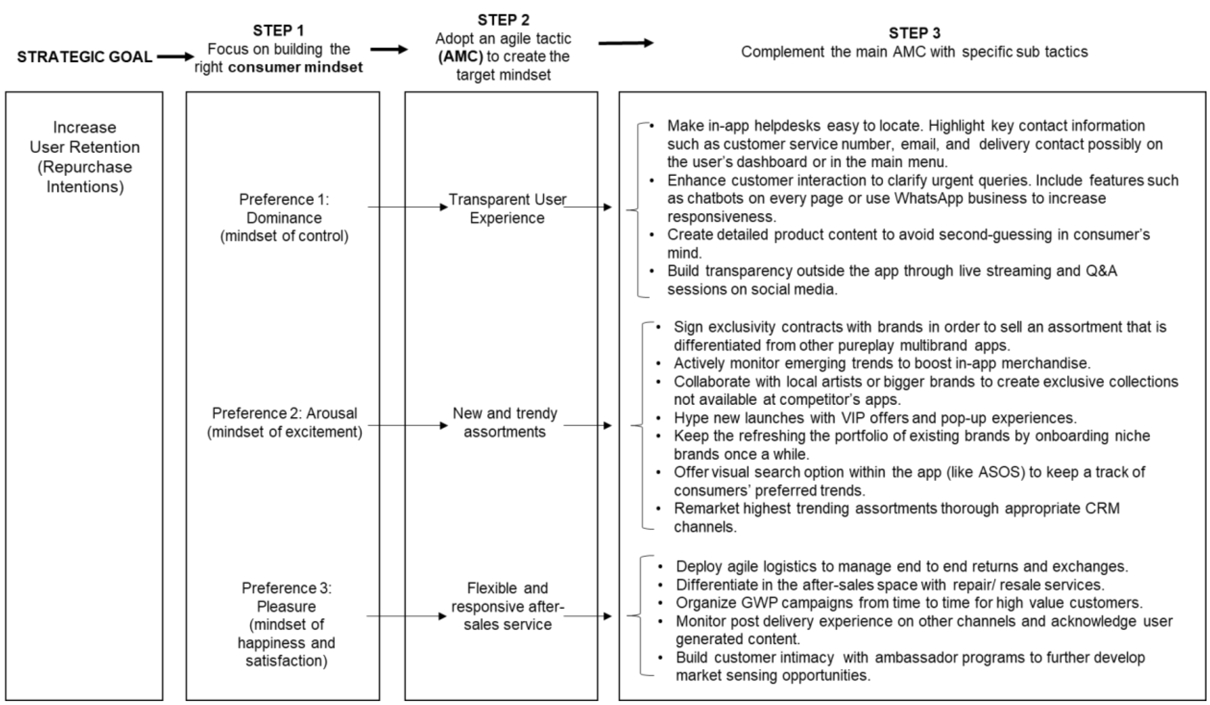

Figure 14: Managerial implications and recommendations.

5.3. Originality and Contribution to Scholarship

To the best of the author's knowledge this is among the first few studies to have empirically examined AMCs from a consumer perspective. The study contributes original consumer insights to a topic that has, till date, been largely explored from an organizational perspective only (Hagen, Zucchella and Ghauri, 2019; Ewel, 2020; Moi and Cabiddu, 2020). The study builds on the seminal theory of environmental psychology (Mehrabian and Russell, 1974), confirming its validity in a new and specific context of pureplay multibrand apps which was not investigated in previous research. By doing so, it widens the scope of both the S-O-R theory (Mehrabian and Russell, 1974) and mobile app usage continuance literature (Bhattacherjee, 2001; Groß, 2016; McLean *et al.*, 2019).

Most importantly, the conceptual model developed in this study contributes to scholarship and industry by providing an explanation about the consumer psychology at play in the interaction between AMCs and repurchase intentions. Specifically, it emphasizes on the feelings of dominance and arousal in driving repeat purchases, concurring with literature (De Canio, Fuentes-Blasco and Martinelli, 2021; Hsieh, Lee and Tseng, 2021; Lim *et al.*, 2021), and further demonstrates how agile cues like platform transparency and newness of assortment can help in eliciting such emotions.

In addition, while other authors such as Hsieh, Lee and Tseng (2021), have explicitly illustrated positive effects of pleasure of app continuance, this study shows that such effects are not statistically significant in the present context. Thus, as suggested by Antwi (2021), this finding shows that perhaps customer satisfaction is a non-differentiator in driving app usage continuance. However, the study does validate the positive effects of an agile after-sales service on consumers' sense of pleasure, for emerging platforms or those struggling with poor customer satisfaction.

One of the key supplementary findings of this study is the significantly low repurchase intentions of the Gen Z cohort which was not observed in previous studies (McLean *et al.*, 2019; De Canio, Fuentes-Blasco and Martinelli, 2021). This is of particular interest to the M-commerce industry in the UAE, in developing retention programs specifically tailored to Gen Zs. In this way, the study provides original geographic insights from the Middle Eastern region which has been largely overlooked in the fashion and app marketing literature, despite its commercial potential and cultural significance (Euromonitor, 2021b). Overall, this study offers a window to organizations rapidly embracing agile manifestos, into what the implications of strategic agility look like from a consumer perspective, and how they may tap into it to build user retention.

5.4. Limitations and areas for further research

Findings from this study under are the constraint of various limitations thereby providing scope for improvement. Firstly, the study is subjected to some design limitations. As is the case with most cross sectional studies, the sample size for this study is relatively low, despite meeting the minimum sample size requirements. Therefore, further studies could be made more robust by including larger sample sizes and performing quota sampling (Bryman and Bell, 2011). Re-designing the study using multi or mixed methods could also produce more robust results (Saunders *et al.*, 2019). In addition, the significant influence of age group on repeat purchases indicates the need to conduct future research in controlled environments to limit the effects of demographics (De Canio, Fuentes-Blasco and Martinelli, 2021).

Secondly, results from this study are specific only to the high street context of pureplay multibrand fashion apps in the UAE. Future research could examine AMCs in a luxury setting, in different geographies to enhance reliability and validity. Given that luxury consumers differ significantly from high street shoppers, and how the luxury segment itself thrives on being rare and exclusive, perhaps there would be some variations between how luxury consumers respond to AMCs (Varley *et al.*, 2019; Desmichela and Kocher, 2020). Future studies could also examine how a concept like agile marketing, largely driven by speed, can be made relevant to emerging areas in fashion such as sustainability and slow fashion, which oppose the very idea of rapid turnover. This would enable industry practitioners to have an understanding about the environmental consequences of running an agile business.

Next, this study investigates only the combined impact of AMCs and consumers' emotional states on repurchase intentions. Future research could separately question the direct impact of AMCs on desired consumer behaviour. This would also open up possibilities to perform mediation analysis so as to compare the differences between direct and indirect influences of AMCs on purchase behaviour (Hair *et al.*, 2014). Theoretically, this study is based on the principles of environmental psychology (Mehrabian and Russell, 1974), examining AMCs as a marketing stimuli in the pureplay environment. Subsequent studies could consider evaluating AMCs from different theoretical perspectives such as the two factor theory used by Lim *et al.* (2021), where in AMCs could be divided into hygiene factors (basic agile necessities) and motivation factors (advanced agile capabilities) to understand how various levels of agile marketing affect consumer behaviour. In line with agility, this research identifies five agile dimensions relevant to the current context. Given the novelty of the research area, other researchers may consider developing agile predictors relevant to their context followed by empirical testing. Lastly, since the effect of pleasure was particularly insignificant on repurchase intentions, other agile predictors could be identified which specifically contribute to feelings of pleasure, such as incentivization and gamification, and revalidate whether or not pleasure influences repeat purchases.

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APPENDIX ONE – RESEARCH ETHICS FORM

NAME: Rutuja Deepraj Jadhav
COLLEGE: London College of Fashion

IF YOUR RESEARCH INVOLVES PARTICIPANTS, PLEASE COMPLETE QUESTIONS 1 TO 9. IF NOT, GO TO QUESTION 10 BELOW.

1. **Will the participants be: (please tick as appropriate)**
- Students at the University ✓ (for pilot survey)
- Participants outside the University ✓
- Other (please specify)

2. **How will participants be recruited and how many will be involved?**

Participants shall be recruited through four social media platforms – LinkedIn, Facebook, WhatsApp, and Instagram. The study is expected to require minimum 100 survey respondents.

3. **What will the participants be asked to do? (Explain in terms appropriate to a lay person)**

Participants will be asked to answer behavioral and attitudinal questions regarding their use of multibrand fashion apps in the U.A.E, by filling in an online questionnaire.

4. **What potential risks to the interests of participants do you foresee and what steps will you take to minimize those risks? (A participant's interests include their physical and psychological well- being, their commercial interests; and their rights of privacy and reputation).**

This study presents minimal risk to participants. One of the risks that may be encountered by participants is relating to their rights of privacy. This shall be minimized by ensuring that all data reported remains anonymous.

5. What potential risks to yourself as research student do you foresee and what steps will you take to minimize those risks? (e.g. does your research raise issues of personal safety for you or others involved in the project, especially if taking place outside working hours or off University premises).

This study presents minimal risk to the researcher. Personal health might be at risk in case of having to collect responses in the field, owing to COVID-19. However, chances of having to conduct a field survey shall be minimized by collecting as many responses as possible online.

6. Please attach a copy of proposed written consent form and information sheet to be given to participants. If you are not obtaining written consent or supplying an information sheet, please explain the reasons for this.

Attached: ✓ (Included on the cover page of the questionnaire).

7. Does your project involve children or vulnerable adults e.g., a person with a learning disability?

- YES/ NO ✓

If YES, you must refer to the Guidance Note on Informed Consent in the Code of Practice on Research Ethics and obtain a Criminal Records Bureau (CRB) check.

Please tick to confirm this has been obtained: N/A

Please refer to the guidance note on data protection available at http://www.arts.ac.uk/research/researching-atual/researcher-support/ before answering the next question. Please consider the value of coding; the importance of secure storage and disposal of personal information, particularly sensitive data (e.g. records of health, origin, criminal record etc.)

8. **Will you be obtaining personal data from any of the participants?**

YES/ **NO ✓ –** only email IDs from respondents intending to participate in the lucky draw. These will not be linked to other answers. Email IDs will be deleted after announcement of the lucky draw winner, at the end of the data collection period.

If YES:

(a) Give details:

(b) How will you store and use this information during the course of your research?

(c) What parts of this information will be confidential?

(d) Will you separate personal identifiers from other (coded) personal data, and if so, how will you safeguard the key?

(e) Will personal data be irreversibly anonymized or, if you have separated the data, will the linking code between the two databases be destroyed?

(f) At the conclusion of your research:

(i) Which of your data sets do you intend to retain personally for use in future research?

(ii) Which do you intend to archive for other researchers?

(iii) Which do you intend to destroy?

(g) Depending on your answers to (f):
(i) If you intend to retain certain data sets for future use or to archive them:
(i.i) How will they be stored?
(i.ii) Will participants be informed what data will be retained, and will their consent be obtained for this – yes

(ii) If you intend to destroy certain data sets at the conclusion of the research:
(ii.i) Explain why this is appropriate –
(ii.ii) How will you ensure that the data will be disposed of in such a way that there is no risk of its confidentiality being compromised?

9. **Will payments to participants be made?** YES/ **NO** ✓

10. **Will any restrictions be placed on the publication of results? YES ✓ /** NO
Yes, all sections of this work shall be subjected to copyright. No sections of this work may be reproduced in any format without the authority of the researcher, the supervisor, and UAL.

11. **I confirm my responsibility to deliver the project in accordance with the Code of Practice on**
Research Ethics of the University of the Arts London (the University). In signing this form, I am also confirming that:
a) The form is accurate to the best of my knowledge and belief.
b) There is no potential material interest that may, or may appear to, impair the independence and objectivity of researchers conducting this project.
c) I undertake to conduct the project as set out in the application unless deviation is agreed by the University and to comply with any conditions set out in the letter sent by the relevant College Research body and/or the University's Research Ethics Sub-Committee.
d) I understand and accept that the ethical propriety of this project may be monitored by the relevant College Research body and/or the University's Research Ethics Sub-Committee.

Signature of
Researcher: Rutuja Deepraj Jadhav Date: 28th July 2021.

12. **I support this project and have reviewed it with the applicant:**
Signature of
Supervisor: _________Cigdem Gogus_____________________________ Date: __30/07/2021________

APPENDIX TWO – PARTICIPANT CONSENT FORM

The following cover page was presented at the start of the survey as an information and consent form for participants.

---

ual: london college of fashion

Information for Survey Participants

What is this survey about?
This survey is being conducted as a part of a Postgraduate research assignment at London College of Fashion, University of the Arts London. The study aims to understand consumer behaviour on Pureplay Multibrand Fashion App platforms in the U.A.E.

What are Pureplay Multibrand Fashion Apps?
A Pureplay Multibrand Fashion App is a mobile application used by online fashion retailers, to sell products from multiple brands under one umbrella store. Some examples of pureplay multibrand e-tailers in the UAE include Namshi, 6th Street, Noon, etc.

Do I need to participate?
Participation in this survey is voluntary. It should take about 3-7 minutes to complete the questionnaire.

Are there any associated benefits?
The survey offers a chance to win an online shopping voucher worth AED 100 to one lucky respondent. Participants interested in this incentive can opt-in to provide their email ID at the end of the survey.

What happens to my data?
All data collected is meant for academic purposes only and shall not be shared with third parties. The responses collected shall be anonymized and recorded in compliance with the GDPR and UAL's privacy policy. Any contact information collected shall be deleted after the announcement of the lucky draw winner.

By proceeding with this questionnaire, you consent to the data collection policies highlighted above and confirm that you are 18, or over 18 years of age.

o Yes
o No

APPENDIX THREE – SUPPORTING CONTENT

A 3.1. Agile Marketing Manifesto

The Agile Marketing Manifesto. Adopted from Ewel (2020).

THE AGILE MARKETING MANIFESTO

- ❑ **Validates learning over opinions and conventions**
- ❑ **Customer-focused collaboration over silos and hierarchy**
- ❑ **Adaptive and iterative-campaigns over big bang campaigns**
- ❑ **The process of customer discover over static prediction**
- ❑ **Flexible over rigid planning**
- ❑ **Responding to change over following a plan**
- ❑ **Many small experiments over a few large bets**

A 3.2. Piloting

Questionnaire amendments post-piloting.

Pre-piloting	**Pilot feedback**	**Post-piloting**
When I use this app, I feel: Relaxed - Excited	“I didn’t understand the relaxed vs excited question”	When I use this app, I feel: Relaxed (laid-back) – Stimulated (energized)
How frequently do you use this app? Where do you mostly use this app?	“Does ‘use’ the app mean use it for activities other than shopping?”	How frequently do you use this app? *'Use' implies both purchase and non-purchase activities such as browsing, information search, etc.* Where do you mostly use this app? *'Use' implies both purchase and non-purchase activities such as browsing, information search, etc.*
Which of the following multibrand fashion apps have you shopped from the most? Please answer the remaining questions based on your usage of this app only.	“I had selected multiple apps when it asked me which app I used frequently. But when the questions said this app, it was confusing since had contradicting opinions about the two apps.”	Changed “allow multiple options” to “allow single option only” in the survey design on Qualtrics.
The after-sales services provided by this app are SLOW.	Observed by author: almost all pilot responses contradicted the subsequent AFS questions. So, this question was reworded to avoid confusion.	The after-sales services provided by this app are FAST.
Call for research was created using a plain text message.	“You can make the call for research more attractive and related to fashion”.	Call for research was amended to look more attractive. Please see images below.

Call for research was amended post-piloting to look more attractive. The new call was designed as follows. Note: All images have been credited with original source on bottom left (vertically).

A 3.3. Sample Size

Minimum sample size determination for Smart PLS using Minimum R^2 method. Adopted from Hair *et al.* (2014). Originally sourced from Cohen (1992).

Maximum Number of Arrows Pointing at a Construct	*Significance Level*											
	1%				*5%*				*10%*			
	Minimum R^2				*Minimum R^2*				*Minimum R^2*			
	0.10	*0.25*	*0.50*	*0.75*	*0.10*	*0.25*	*0.50*	*0.75*	*0.10*	*0.25*	*0.50*	*0.75*
2	158	75	47	38	110	52	33	26	88	41	26	21
3	176	84	53	42	124	59	38	30	100	48	30	25
4	191	91	58	46	137	65	42	33	111	53	34	27
5	205	98	62	50	147	70	45	36	120	58	37	30
6	217	103	66	53	157	75	48	39	128	62	40	32
7	228	109	69	56	166	80	51	41	136	66	42	35
8	238	114	73	59	174	84	54	44	143	69	45	37
9	247	119	76	62	181	88	57	46	150	73	47	39
10	256	123	79	64	189	91	59	48	156	76	49	41

A 3.4. Proposed Sampling Quota

Originally proposed quota for sampling. Later discarded since sampling strategy was changed from quota to a combination of convenience and snowball sampling (self-selection).

Population figures for the UAE obtained from Global Data (2020).

Target Population: 2,808,990 | Actual Population: 9,890,402					
Indicators		**Population**	**% of Target Population**	**% of Quota (N= 200)**	**Sum in Quota**
GENDER	**AGE**				
F	20-24	143,258.49	5%	5%	**10**
F	25-29	244,382.13	9%	9%	**17**
F	30-34	455,056.38	16%	16%	**32**
Female Total		842,697.00	30%	30%	**60**
M	20-24	334,269.81	12%	12%	**24**
M	25-29	570,224.97	20%	20%	**41**
M	30-34	1,061,798.22	38%	38%	**76**
Male Total		1,966,293.00	70%	70%	**140**
Total		2,808,990.00	100%	100%	**200**

A 3.5. Questionnaire

SCREENING QUESTIONS						
Are you currently based in the U.A.E?	o Yes	o No (skip to end of survey)				
Have you shopped at least once in the past two years using any of the following multibrand fashion apps? - 6th Street / Namshi / Noon/ Sivvi / Styli.	o Yes	o No (skip to end of survey)				
BLOCK 1						
Which of the following multibrand fashion apps have you shopped from the most? *Please answer the remaining questions based on your usage of this app only.*	o 6th Street	o Namshi	o Noon	o Styli	o Sivvi	
What is your purpose of using this multibrand fashion app? Select all that apply	o Browsing for new styles and trends	o Information Search	o Purchasing Products	o Order Management	o Being up-to-date on discounts and offers	o Other (please specify)
How frequently do you use this app? *'Use' implies both purchase and non-purchase activities such as browsing, information search, etc.*	o At least once a week	o At least once a month	o At least once in three months	o At least once in six months	o At least once a year	o At least once in two years
Where do you mostly use this app? *'Use' implies both purchase and non-purchase activities such as browsing, information search, etc.*	o At home	o At place of work	o A place of study (school/ college/ university)	o While commuting (on the go)	o Other (please specify)	
BLOCK 2						
Please indicate your level of disagreement/ agreement with each of the following statements:						
Newness of Assortment	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	
This app sells various trendy fashion assortments.	o	o	o	o	o	
This app offers fashion products with new designs.	o	o	o	o	o	
This app is up to date with new product launches.	o	o	o	o	o	
Please select the 'Neutral' option for this statement. This is just to screen out random clicking.	o	o	o	o	o	
Personalization	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	
There are personalized contents in this app.	o	o	o	o	o	
This app personalizes product recommendations to suit my taste.	o	o	o	o	o	

This app displays personalized advertisements based on my usage.	o	o	o	o	o	
Transparent User Experience	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	
I know when my order has been shipped or is being compiled using this app.	o	o	o	o	o	
The delivery information is readily available when using this app.	o	o	o	o	o	
I know when my order has been received using this app.	o	o	o	o	o	
This app has a transparent payment procedure.	o	o	o	o	o	
Ubiquity of the App	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	
I can use this app anytime.	o	o	o	o	o	
I can use this app anywhere.	o	o	o	o	o	
I expect the app would be available to use whenever I need it.	o	o	o	o	o	
After-Sales Service	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	
The after-sales services provided by this app are fast.	o	o	o	o	o	
The return/ exchange process using this app is fast.	o	o	o	o	o	
This app is quick to process any refund requests.	o	o	o	o	o	

When I use this app, I feel:

Sleepy	o	o	o	o	o	Active
Calm	o	o	o	o	o	Excited
Relaxed (laid-back)	o	o	o	o	o	Stimulated (energized)
Unhappy	o	o	o	o	o	Happy
Annoyed	o	o	o	o	o	Pleased
Dissatisfied	o	o	o	o	o	Satisfied

Please indicate your level of disagreement/ agreement with each of the following statements:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I feel like I have a lot of control over my usage experiences on this app	o	o	o	o	o
When I am on this app, I can choose freely what I want to see	o	o	o	o	o
While using the app, my actions decide the kind of experiences I get on this app	o	o	o	o	o
	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
When I shop for fashion products online, I consider this app first.	o	o	o	o	o
I do most of my online fashion shopping using this app.	o	o	o	o	o
If I could shop online today, I would shop from this app again.	o	o	o	o	o

I plan to do most of my future shopping from this app.	o	o	o	o	o	
BLOCK 3						
How do you identify yourself?	o Male	o Female	o Prefer not to disclose			
Which age group do you belong to?	o 18 -24 years	o 25 - 29 years	o 30 - 34 years	o 35 - 39 years	o 40 years or above	o Other (please specify)
What is your occupation?	o Student	o Public-sector employed	o Private-sector employed	o Self-employed	o House / Family Manager	
	o Unemployed	o Prefer not to disclose				

A 3.6. Frequencies of responses obtained.

- **Frequencies obtained for behavioural questions:**

Table 32: Frequencies of app used.

Which of the following multibrand fashion apps have you shopped from the most? *Please answer the remaining questions based on your usage of this app only.*		
	Frequency	**Percent**
6th Street	14	10.9
Namshi	76	59.4
Noon Fashion	32	25.0
Sivvi	4	3.1
Styli	2	1.6
Total	128	100.0

Table 33: App usage frequency.

How frequently do you use this app? *'Use' implies both purchase and non-purchase activities such as browsing, information search, etc.*		
	Frequency	**Percent**
At least once a week	37	28.9
At least once a month	46	35.9
At least once in three months	24	18.8
At least once in six months	14	10.9
At least once a year	3	2.3
At least once in two years	4	3.1
Total	128	100.0

Table 34: App usage location

Where do you mostly use this app? *'Use' implies both purchase and non-purchase activities such as browsing, information search, etc.*		
	Frequency	**Percent**
At home	104	81.3
At place of work	12	9.4
At place of study (school/ college/ university)	3	2.3
While commuting (on the go)	9	7.0
Total	128	100.0

- **Frequencies obtained for demographic questions:**

Table 35: Frequencies for gender.

How do you identify yourself?		
	Frequency	**Percent**
Male	25	19.5
Female	98	76.6
Prefer not to disclose	5	3.9
Total	128	100.0

Table 36: Frequencies for age groups.

Which age group do you belong to?		
	Frequency	**Percent**
18 - 24 years	50	39.1
25 - 29 years	53	41.4
30 - 34 years	25	19.5
Total	128	100.0

Table 37: Frequencies for occupation.

What is your occupation?		
	Frequency	**Percent**
Student	25	19.5
Public sector-employed	6	4.7
Private sector-employed	78	60.9
Self-employed	12	9.4
House manager/ Family manager	1	0.8
Unemployed	4	3.1
Prefer not to disclose	2	1.6
Total	128	100.0

- **Frequencies obtained for constructs used in hypotheses testing:**

Table 38: Frequencies for main constructs.

Construct	Scale Items		Strongly Disagree / Disagree		Neutral		Strongly Agree / Agree		Total
			Frequency	Percent	Frequency	Percent	Frequency	Percent	
Newness of Assortment	NoA_1	This app sells various trendy fashion assortments.	3	2.3%	23	18.0%	102	79.7%	128
	NoA_2	This app offers fashion products with new designs.	8	6.3%	26	20.3%	94	73.4%	128
	NoA_3	This app is up to date with new product launches.	8	6.3%	32	25.0%	88	68.8%	128
Personalization	PER_1	There are personalized contents in this app.	29	22.7%	43	33.6%	56	43.8%	128
	PER_2	This app personalizes product recommendations to suit my taste.	25	19.5%	35	27.3%	68	53.1%	128
	PER_3	This app displays personalized advertisements based on my usage.	12	9.4%	28	21.9%	88	68.8%	128
Transparent User Experience	TUX_1	I know when my order has been shipped or is being compiled using this app.	5	3.9%	13	10.2%	110	85.9%	128
	TUX_2	The delivery information is readily available when using this app.	1	0.8%	17	13.3%	110	85.9%	128
	TUX_3	I know when my order has been received using this app.	2	1.6%	9	7.0%	117	91.4%	128
	TUX_4	This app has a transparent payment procedure.	0	0.0%	13	10.2%	115	89.8%	128
Ubiquity	UBQ_1	I can use this app anytime.	2	1.6%	10	7.8%	116	90.6%	128
	UBQ_2	I can use this app anywhere.	0	0.0%	7	5.5%	121	94.5%	128
	UBQ_3	I expect the app would be available to use whenever I need it.	2	1.6%	7	5.5%	119	93.0%	128
After-Sales Service	AFS_1	The after-sales services provided by this app are fast.	12	9.4%	48	37.5%	68	53.1%	128
	AFS_2	The return/ exchange process using this app is fast.	6	4.7%	51	39.8%	71	55.5%	128
	AFS_3	This app is quick to process any refund requests.	12	9.4%	48	37.5%	68	53.1%	128
			Sleepy / Calm / Relaxed		*Neutral*		*Active / Excited / Stimulated*		
Arousal	ARO_1	When I use this app I feel: Sleepy - Active	14	10.9%	37	28.9%	77	60.2%	128
	ARO_2	When I use this app I feel: Calm - Excited	19	14.8%	56	43.8%	53	41.4%	128
	ARO_3	When I use this app I feel: Relaxed (laid-back) - Stimulated (Energized)	46	35.9%	43	33.6%	39	30.5%	128
Dominance	DOM_1	I feel like I have a lot of control over my usage experiences on this app	12	9.4%	32	25.0%	84	65.6%	128
	DOM_2	When I am on this app, I can choose freely what I want to see	6	4.7%	14	10.9%	108	84.4%	128
	DOM_3	While using the app, my actions decide the kind of experiences I get on this app	9	7.0%	26	20.3%	93	72.7%	128
			Unhappy / Annoyed / Dissatisfied		*Neutral*		*Happy / Pleased / Satisfied*		
Pleasure	PLE_1	When I use this app I feel: Unhappy - Happy	3	2.3%	27	21.1%	98	76.6%	128
	PLE_2	When I use this app I feel: Annoyed - Pleased	9	7.0%	35	27.3%	84	65.6%	128
	PLE_3	When I use this app I feel: Dissatisfied - Satisfied	7	5.5%	31	24.2%	90	70.3%	128
Repurchase Intentions	RPI_1	When I shop for fashion products online, I consider this app first.	23	18.0%	36	28.1%	69	53.9%	128
	RPI_2	I do most of my online fashion shopping using this app.	45	35.2%	31	24.2%	52	40.6%	128
	RPI_3	If I could shop online today, I would shop from this app again.	22	17.2%	34	26.6%	72	56.3%	128
	RPI_4	I plan to do most of my future shopping from this app.	31	24.2%	43	33.6%	54	42.2%	128

A 3.7. Normality tests for all constructs.

- Normality descriptives for all constructs. Mean and 5% Trimmed Mean values are almost equal, indicating RPI data is normally distributed. Skewness and Kurtosis are within acceptable -1 and +1 limits for normality.

Table 39: Normality descriptives for main constructs.

Constructs	**Mean** Statistic Std. Error	**95% C.I for Mean** Lower Bound Upper Bound	**5% Trimmed Mean**	**Skewness** Statistic Std. Error	**Kurtosis** Statistic Std. Error
NoA	3.804 0.048	3.708 3.901	3.807	-0.284 0.214	0.613 0.425
PER	3.440 0.058	3.323 3.556	3.457	-0.386 0.214	-0.031 0.425
TUX	4.224 0.051	4.121 4.327	4.246	-0.160 0.214	-0.777 0.425
UBQ	4.283 0.048	4.187 4.380	4.307	-0.108 0.214	-0.576 0.425
AFS	3.679 0.070	3.539 3.819	3.703	-0.026 0.214	0.228 0.425
PLE	3.932 0.066	3.801 4.063	3.969	-0.431 0.214	-0.051 0.425
ARO	3.343 0.077	3.189 3.497	3.34	0.138 0.214	-0.454 0.425
DOM	3.786 0.050	3.686 3.886	3.794	-0.432 0.214	0.935 0.425
RPI	3.300 0.069	3.162 3.439	3.295	-0.074 0.214	-0.681 0.425

- Kolmogorov-Smirnov and Shapiro-Wilk's test for normality of all constructs. ($p < 0.05$ significance level). Although Kolmogorov-Smirnov and Shapiro-Wilk statistic are significant ($p < 0.05$), indicating violation of normality, such results are usually observed in larger samples.

Table 40: Normality tests for main constructs.

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
Constructs	Statistic	df	Sig.	Statistic	df	Sig.
NoA	0.185	128	0.000	0.929	128	0.000
PER	0.136	128	0.000	0.962	128	0.001
TUX	0.196	128	0.000	0.911	128	0.000
UBQ	0.267	128	0.000	0.856	128	0.000
AFS	0.142	128	0.000	0.933	128	0.000
PLE	0.130	128	0.000	0.946	128	0.000
ARO	0.105	128	0.001	0.969	128	0.004
DOM	0.216	128	0.000	0.914	128	0.000
RPI	0.107	128	0.001	0.967	128	0.003

a. Lilliefors Significance Correction

A 3.8. Normality Plots

- Normality Plots for NoA.

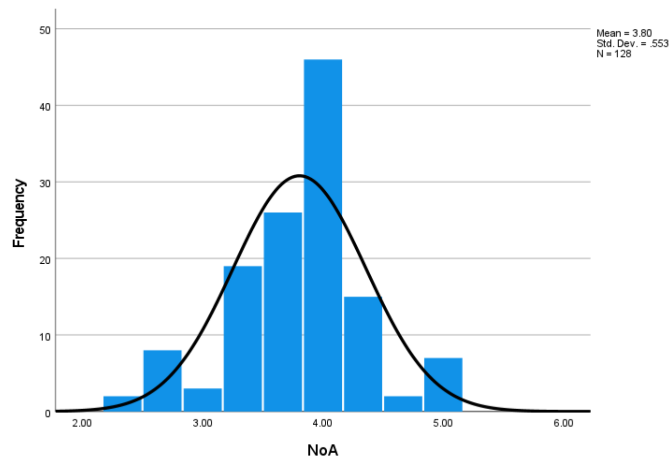


Figure 15: Histogram plot and normality curve for NoA scores.

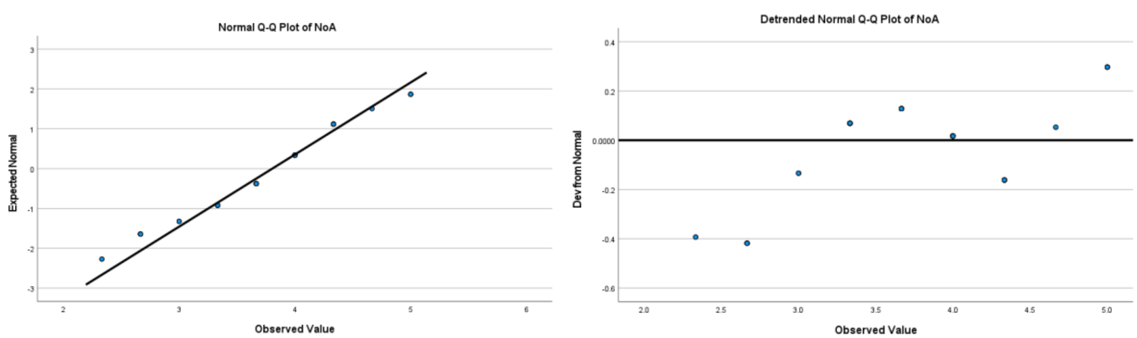


Figure 16: Normal Q-Q plot and Detrended Normal Q-Q plot for NoA.

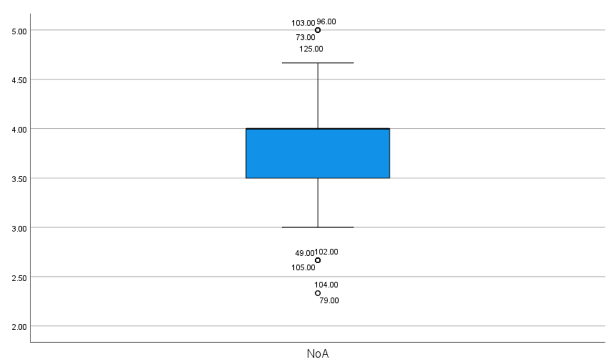


Figure 17: Box Plot for NoA indicating presence of outliers.

- Normality Plots for PER

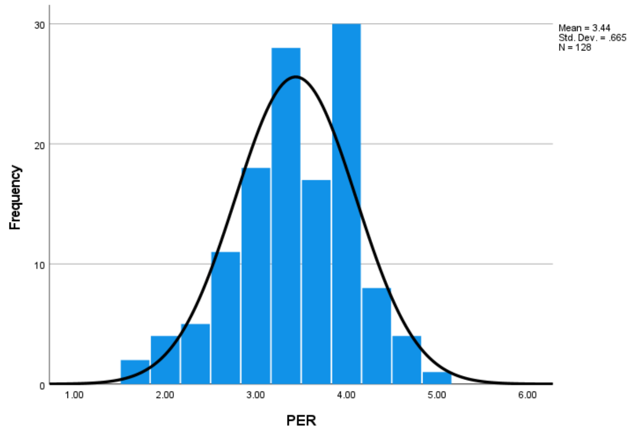


Figure 18: Histogram plot and normality curve for PER scores.

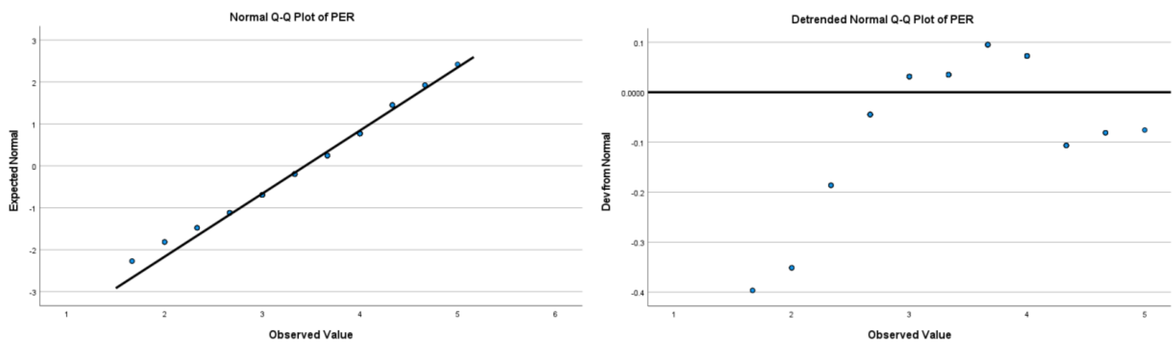


Figure 19: Normal Q-Q plot and Detrended Normal Q-Q plot for PER.

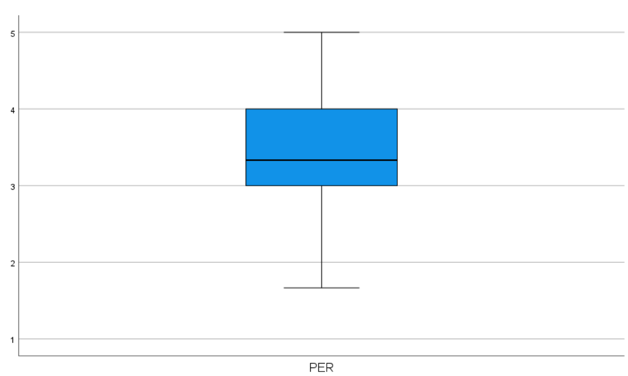


Figure 20: Box Plot for PER.

- Normality Plots for TUX

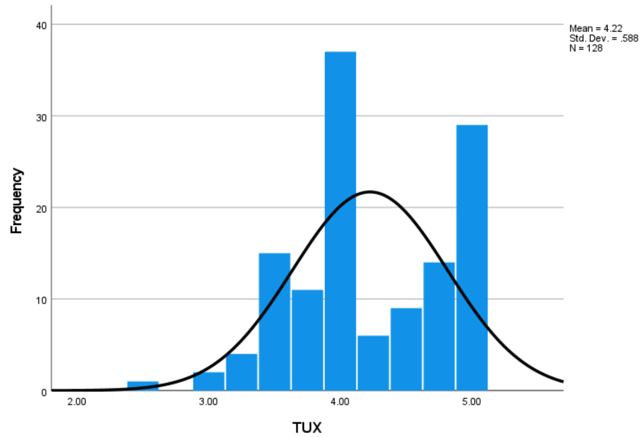


Figure 21: Histogram plot and normality curve for TUX scores.

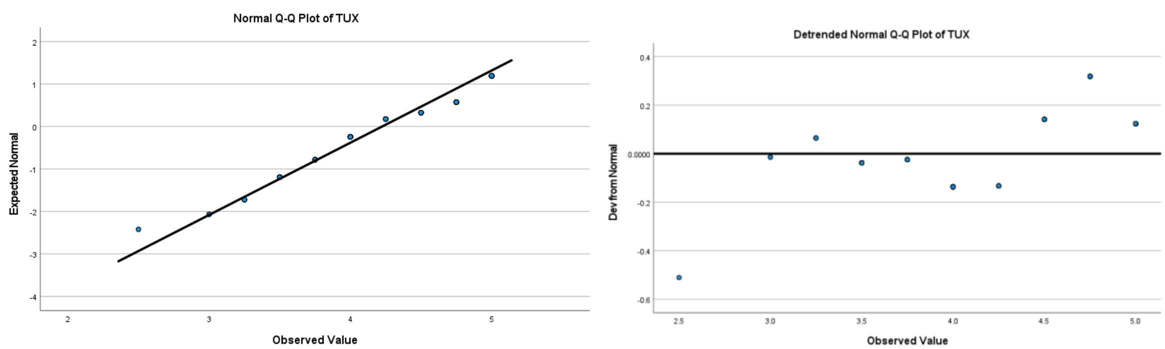


Figure 22:Normal Q-Q plot and Detrended Normal Q-Q plot for TUX.

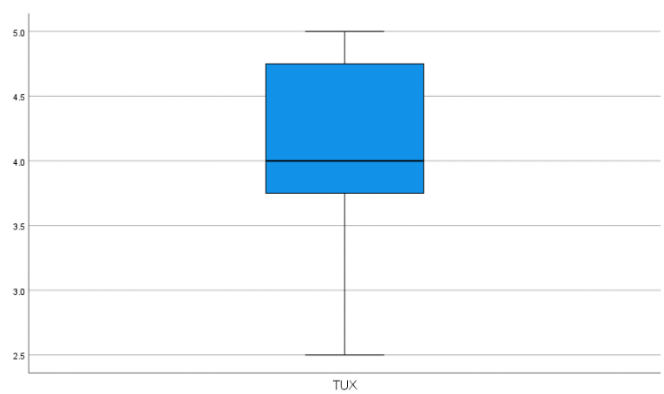


Figure 23: Box Plot for TUX.

- Normality plots for UBQ

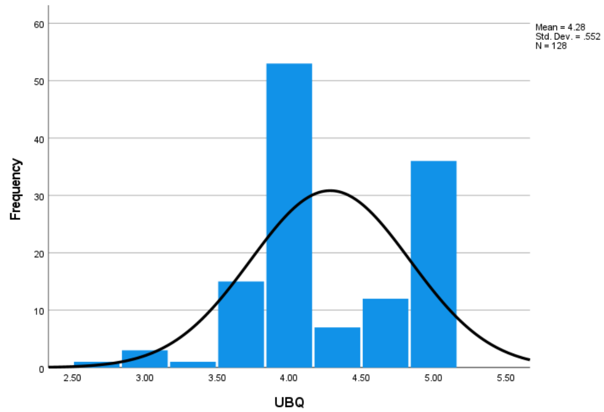


Figure 24: Histogram plot and normality curve for UBQ scores.

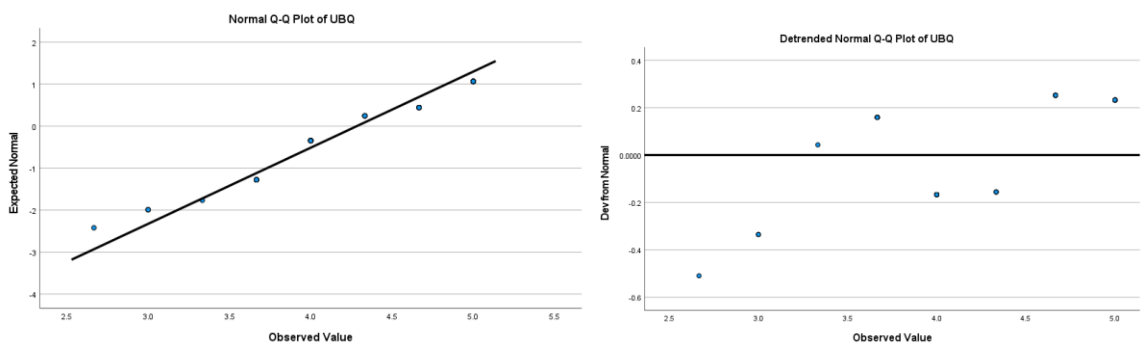


Figure 25: Normal Q-Q plot and Detrended Normal Q-Q plot for UBQ.

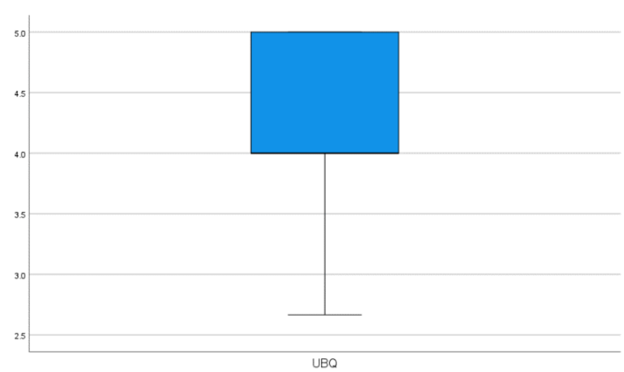


Figure 26: Box Plot for UBQ.

- Normality plots for AFS

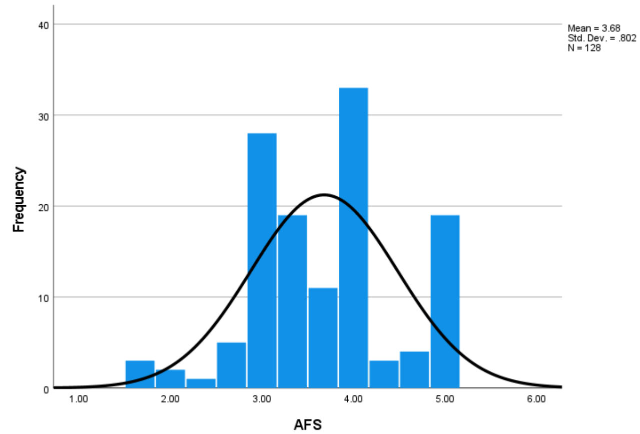


Figure 27: Histogram plot and normality curve for AFS.

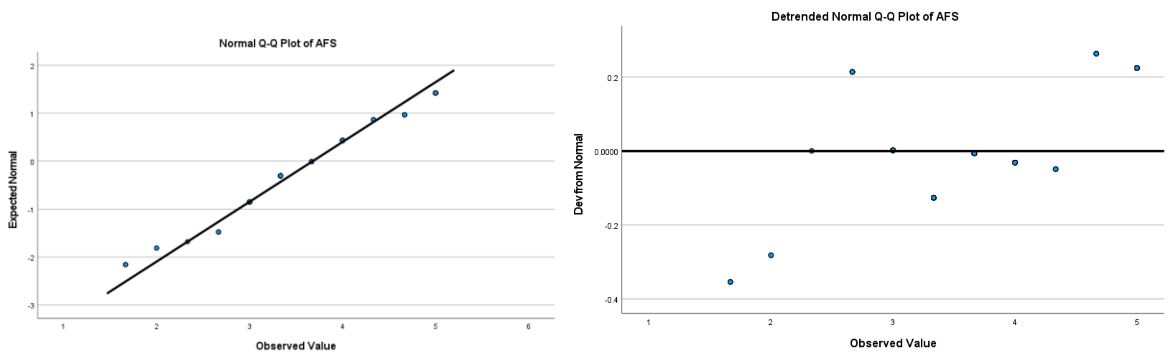


Figure 28: Normal Q-Q plot and Detrended Normal Q-Q plot for AFS.

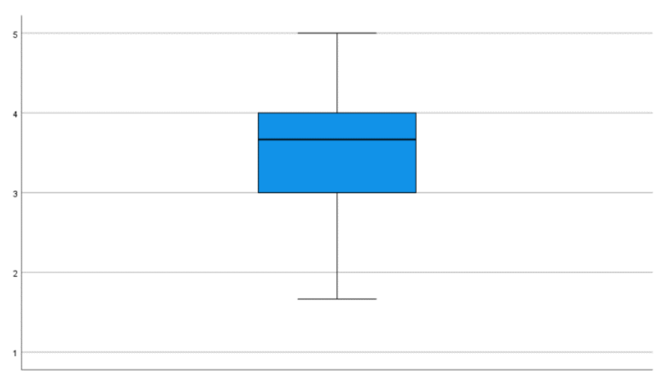


Figure 29: Box Plot for AFS.

- Normality plots for PLE

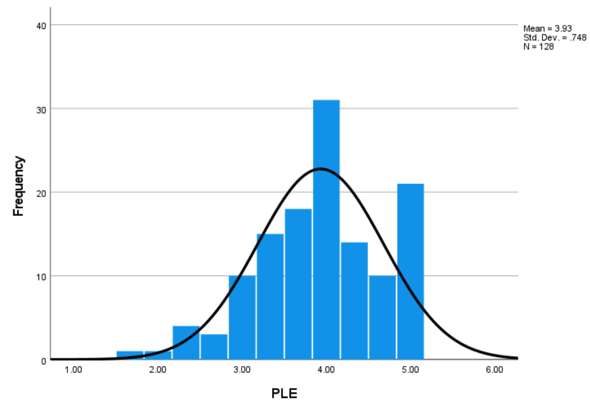


Figure 30: Histogram plot and normality curve for PLE scores.

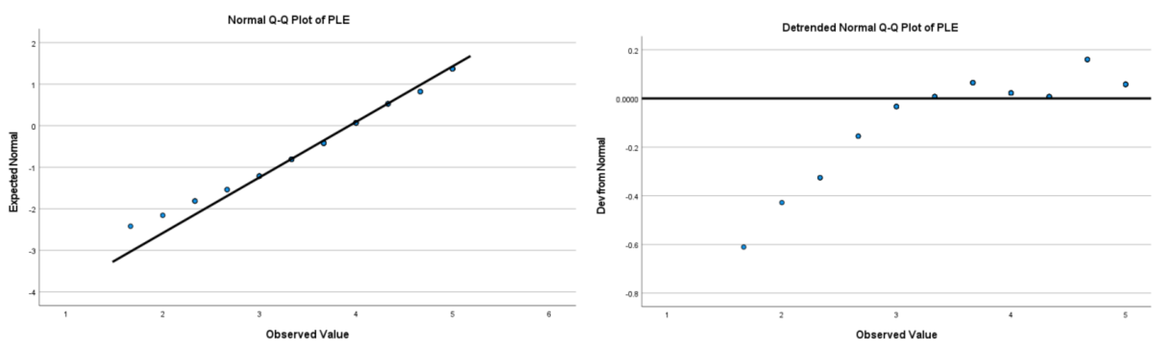


Figure 31: Normal Q-Q plot and Detrended Normal Q-Q plot for PLE.

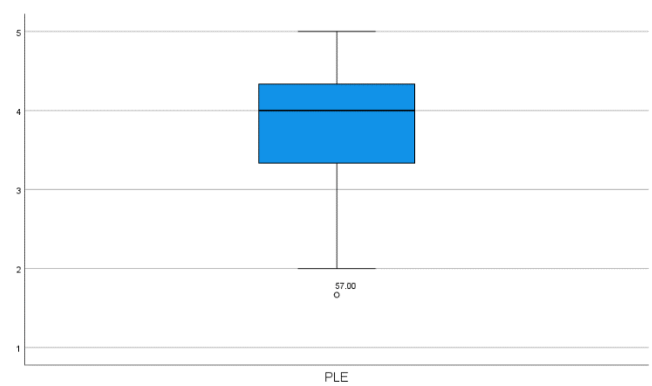


Figure 32: Box Plot for PLE.

* Normality plots for ARO

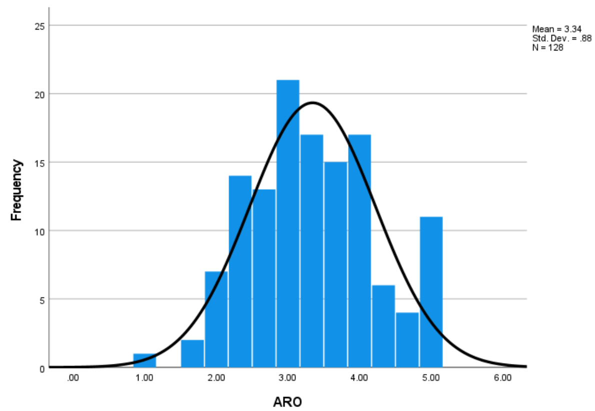
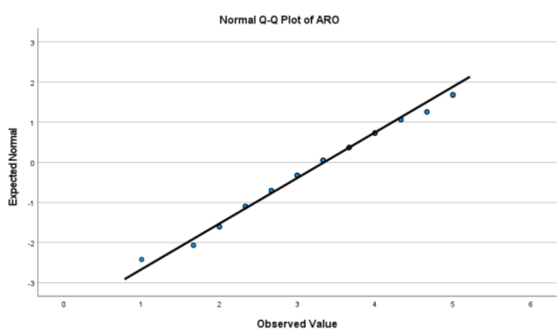


Figure 33L Histogram plot and normality curve for ARO scores.



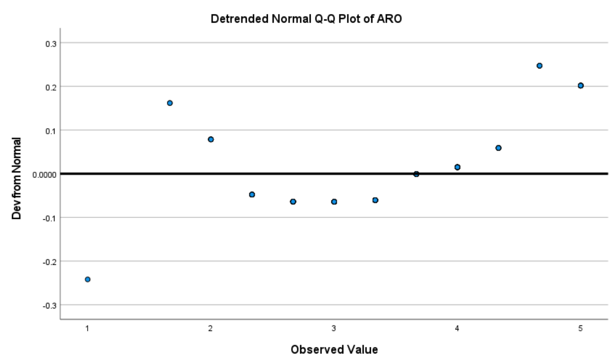


Figure 34: Normal Q-Q plot and Detrended Normal Q-Q plot for ARO.

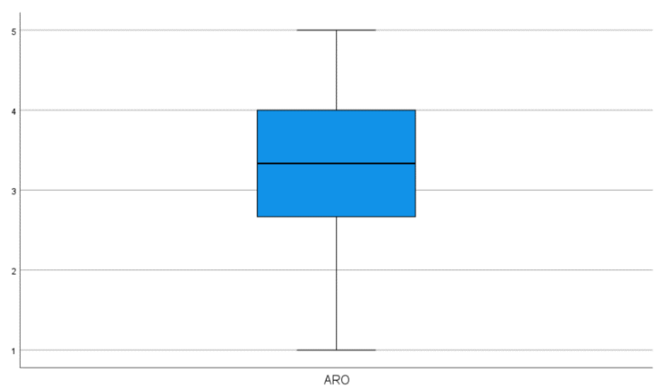


Figure 35: Box Plot for ARO.

- Normality plots for DOM

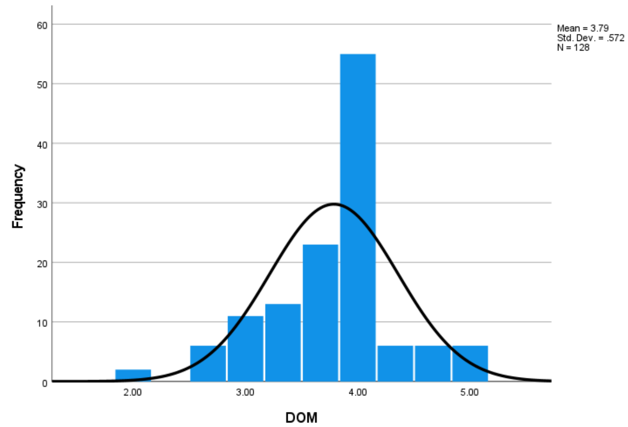


Figure 36: Histogram plot and normality curve for DOM scores.

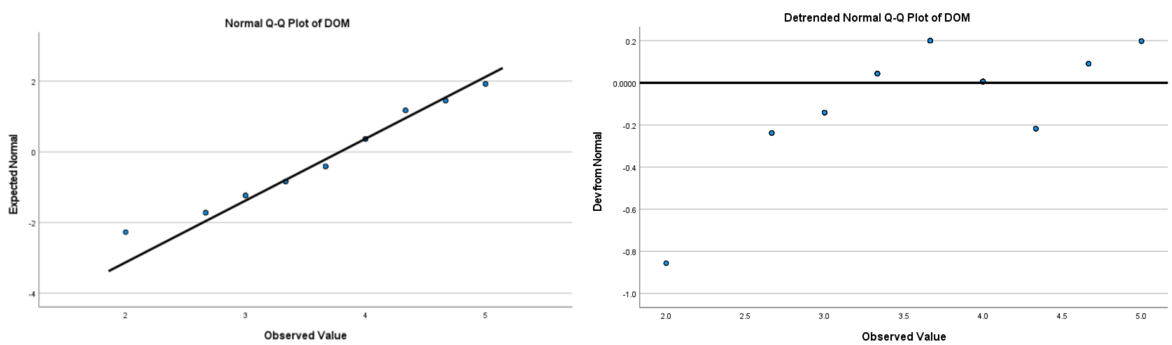


Figure 37: Normal Q-Q plot and Detrended Normal Q-Q plot for DOM.

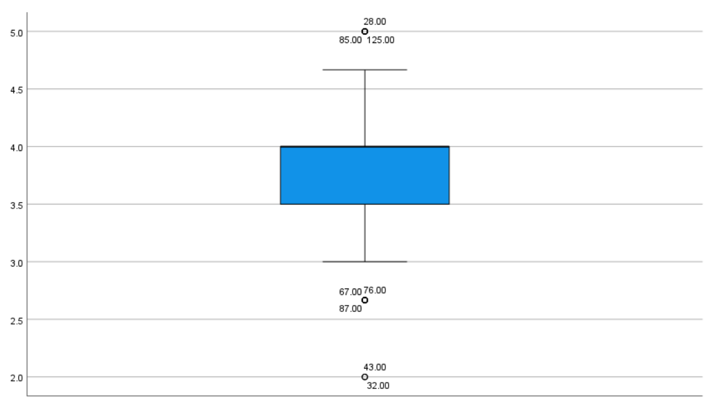


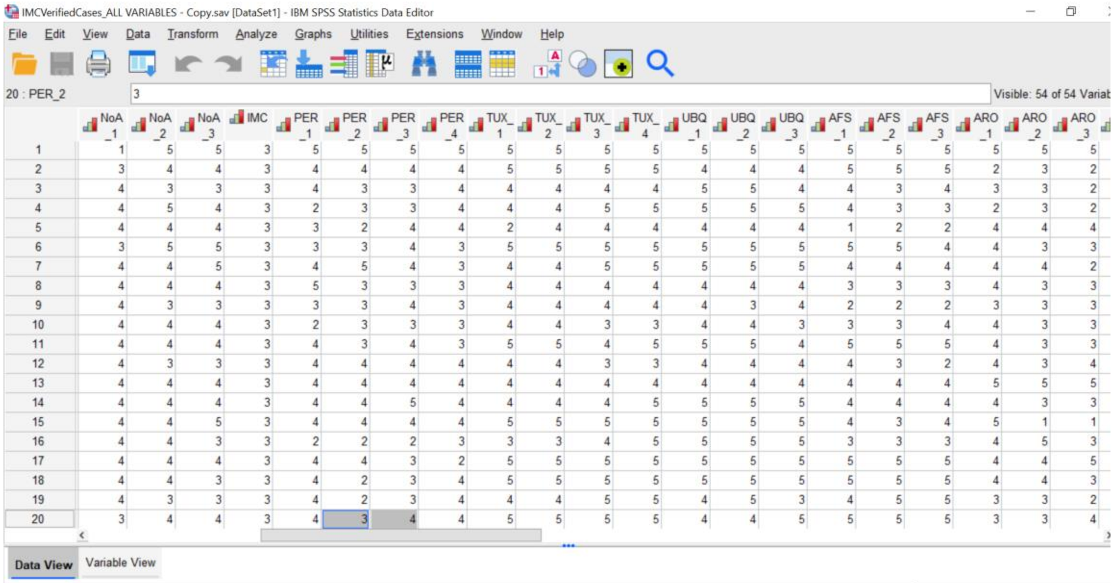
Figure 38: Box Plot for DOM.

- Normality plots for RPI – Refer Chapter 4.

A 3.9. Harman's one-factor test for evaluating CMB.

Total Variance Explained						
	Initial Eigenvalues			**Extraction Sums of Squared Loadings**		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.982	26.605	26.605	7.982	**26.605**	26.605
2	3.489	11.629	38.234			
3	2.376	7.920	46.154			
4	1.864	6.213	52.367			
5	1.531	5.103	57.470			
6	1.361	4.538	62.008			
7	1.085	3.618	65.625			
8	0.985	3.282	68.908			
9	0.940	3.133	72.040			
10	0.837	2.789	74.829			
11	0.783	2.610	77.438			
12	0.700	2.334	79.772			
13	0.627	2.089	81.861			
14	0.590	1.966	83.828			
15	0.550	1.833	85.661			
16	0.533	1.775	87.436			
17	0.468	1.561	88.997			
18	0.446	1.486	90.483			
19	0.404	1.346	91.829			
20	0.364	1.215	93.044			
21	0.325	1.084	94.127			
22	0.289	0.963	95.091			
23	0.267	0.892	95.982			
24	0.261	0.872	96.854			
25	0.206	0.686	97.540			
26	0.201	0.670	98.209			
27	0.164	0.546	98.755			
28	0.143	0.475	99.230			
29	0.129	0.431	99.661			
30	0.102	0.339	100.000			
Extraction Method: Principal Component Analysis.						

A 3.10. Screenshot of raw data from SPSS



IMCVerifiedCases_ALL VARIABLES - Copy.sav [DataSet1] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

20 : PER_2 3

Visible: 54 of 54 Variab

	NoA_1	NoA_2	NoA_3	IMC	PER_1	PER_2	PER_3	PER_4	TUX_1	TUX_2	TUX_3	TUX_4	UBQ_1	UBQ_2	UBQ_3	AFS_1	AFS_2	AFS_3	ARO_1	ARO_2	ARO_3
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Data View Variable View